Title

Non-Constant Learning Rates in Retrospective Experience Curve Analyses and their Correlation to Deployment Programs

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Abstract: A key challenge for policy-makers is estimating future technology costs and the rate of cost reduction versus production volume. A related critical question is what role state and federal governments should have in advancing energy efficient and renewable energy technologies. We derive learning rates for six technologies (electronic ballasts, magnetic ballasts, compact fluorescent lighting, general service fluorescent lighting, stationary fuel cells, and the installed price of residential solar PV) and provide an overview and timeline of historical deployment programs, such as state and federal standards and incentive programs, for each technology. Piecewise linear regimes are observed in a range of technology experience curves, and deployment programs are found to be strongly correlated to an increase in learning rate across multiple technologies. A downward bend in the experience curve is found in 5 out of the 6 energy-related technologies presented here. In each of the five downward-bending experience curves, we believe that an increase in the learning rate can be linked to deployment programs to some degree. This work sheds light on the endogenous versus exogenous contributions to technological innovation and can inform future policy investment direction and can shed light on market transformation and technology learning behavior.

Key words: Experience curves, learning rates, deployment programs, technology costs, technology innovation.

1. Introduction

A key question for policy makers is deciding what role the state and federal government should play in advancing technology and energy efficient and renewable energy technologies in particular. Should they invest in research, development or deployment; how should they invest, and in which technologies? For technologies in the early commercialization phase, deployment programs can increase market adoption and can signal to industrial firms a commitment by the government to advance that technology. This provides a greater degree of market certainty and supplier firms are more likely to make long-term investments in the technology, reducing cost and further increasing market adoption. However, there is a

lack of data in quantifying the impact of deployment programs to technology learning and innovation as well as quantification of the technology cost reductions that can result from deployment programs, and thus it is difficult to ascertain where and how the state or federal government should support deployment programs.

This study begins to address these questions by constructing experience curves and deriving learning rates for eight technologies with as much empirically available evidence as possible. Through data collection and assemblage of historical deployment programs, we are able to develop new or updated experience curves for each technology and summarize observed changes in the slope of the price-based experience curves (i.e. the learning rates). We also summarize data availability and trends and overlay historical deployment programs and other activity on the compiled experience curves in an attempt to understand and describe what factors can trigger a change in the slope. With this information, we provide interpretations for the role that government programs can play in inducing changes in experience curve behavior. We believe this longitudinal assessment of energy-related technologies and using a consistent analysis approach for each of the technologies is the largest reported in the open literature, to our knowledge.

1.1 Experience Curves

Technology learning is widely accepted as a mechanism through which technology costs reductions can occur, a concept originating from observations that manufacturing processes improve as production increases (Wright, 1936). This has important implications for understanding past technology developments and program benefits, as well as forecasting technology market growth for policy planning and scenario modeling.

Experience curves are the most common framework for assessing technology learning and cost reduction with increasing production volume. These curves are thought to follow a power law, with the rate of cost reduction a power law function of cumulative production volume:

$$C(t_2)/C(t_1) = (V(t_2)/V(t_1))^{-b}$$

where

$C(t_2)$ = cost at time t_2 and $V(t_2)$ = cumulative production volume at time t_2

$C(t_1)$ = cost at time t_1 and $V(t_1)$ = cumulative production volume at time t_1

and b is an empirically observed parameter. For every doubling in cumulative production volume,

$$C(t_2)/C(t_1) = 2^{-b}$$

The percent by which cost decreases for every doubling of production is referred to as the learning rate ($LR = 1 - 2^{-b}$), while the fraction of initial cost after every doubling of production is defined as the progress ratio ($PR = 1 - LR$) (Wright, 1936).

Learning curves, which directly relate cumulative production to labor costs, are a subset of experience curves, which relate cumulative production to overall cost or price (although the terms “learning curve” and “experience curve” are often used interchangeably). Therefore, learning curves reflect short-run learning-by-doing, while experience curves incorporate a much broader set of cost components (Hall, 1985). Shifts in production cost may be reflected in the experience curve by a change in the learning rate, or slope of the curve.

Experience curves are commonly fit as a single power law, with the learning rate derived from the exponent of the resulting equation (Weiss et al., 2009). In our broad study of historic energy technology development, we find that many experience curves can be better fit with piecewise power laws, indicating a change in the learning rate at some point in time. We discuss development of these experience curves and implications of changing learning rates for program analysis and technology projections.

Market prices are often utilized as a proxy for a product’s manufactured costs since market prices are more directly observable than manufacturing costs. However, prices can mask the cost structure of a

product and introduce uncertainties in the product's technology learning due to pricing and market effects. Despite these caveats, market prices are often used for experience curve analyses.

1.2 Cost reduction drivers and deployment programs

A technology's cost reductions are driven by a complex interplay of many factors: process and manufacturing technology learning, economies of scale, product innovations in design, packaging, and assembly, and increased research and development investment. An interconnected set of market and technology factors can act to generate these cost reductions. For example, increased market adoption from improved product design and performance can lead to greater investments in production and economies of scale and "learning by doing"; new market entrants and component or material suppliers can provide competitive pressures to market pricing and supply chain costs; and exogenous factors can play a role in lowering factor input costs or by increasing the costs of competing technologies.

Finally, there is the role of public policy programs which can act in various ways to ultimately encourage lower technology costs. Investment in R&D can stimulate product and process innovation while deployment programs can encourage greater market adoption through the use of informational campaigns, customer incentives, or demonstration programs. Deployment programs contribute to technology development through a number of modes, such as increasing adoption and encouraging development of new or improved products.

Deployment programs have been identified as a key activity for emerging energy-related technologies in the pilot/early commercialization stage of the research, development and deployment cycle. Here, deployment is defined fairly broadly and can include incentive programs, state and federal standards, design contests, state and federal procurement, information and education programs, public testing and performance databases, and so on. Experience curves are a useful depiction for cost reduction data, showing cost reductions in relation to production quantities (and therefore adoption rates). These curves can then be used to relate cost reduction goals to adoption targets. For example, a policy maker or

supplier firm with a technology roadmap may define a cost target by a certain date. In order to reach this target, the technology must “move down” the experience curve by increasing market adoption and therefore realizing “learning-by-doing” improvements (e.g., improvements in the manufacturing process) or other technological improvements. Projecting forward with the learning rate (LR) demonstrated by the historical experience curve will thereby set a market adoption target by the target date, and this will serve as guidance for setting incentives or other deployment programs for the policy maker. Thus extrapolation and interpretation of the existing experience curve can have a large impact on achieving a cost vs. time target, and understanding if, when, and how learning rates change is critical to policy planning and goal setting. Conversely, historical experience curves may provide the opportunity to retrospectively relate learning rates to deployment programs and other factors.

1.3 Canonical experience curves

Shifts in product price versus cumulative output are shown schematically in Figure 1 below (Boston Consulting Group, 1968). Experience curves are typically presented on a log-log plot, i.e., the y-axis is plotted as the log of price or cost and the x-axis is plotted as the log of cumulative output and the slope is related to the learning rate. The dotted line in this case represents direct manufacturing costs with the difference between the price and cost lines representing the product margin. This curve illustrates the possible differences in observed price learning behavior and underlying cost structure. The cost curve is driven by multiple factors described above while the price curve may be controlled by the market environment, competitive environment, pricing power, and other factors. An empirically observed price curve may have regions of different linear slopes. For example, the cost of production may exceed the initial price during the development phase in order to capture market share. A “price umbrella” region may result if the producer has a unique product and market pricing power. With a more established supply chain and increasing output direct costs fall and effective margins are seen to increase. A “shakeout” region of steeply falling price can result with new market entrants, creating pricing pressure and a steep drop in prices.

A new regime is reached in the price learning slope in the “stability” region where margins are reduced and price and cost track more closely (point C forward). Note also that Figure 1 applies canonically to new product introduction, but it is possible to have a downward shift in the price experience curve in a relatively mature market (point D) as we will see which is presumably accompanied by a downward shift in the cost curve. A key question for this work is to understand and describe what factors can trigger a change in slope of the price-based experience curve – often ascribed to market shakeout from increased competition in early product introduction as described above, but also possible in more mature markets. Note however that the price experience curve can only be used to infer technology learning or innovation unless more information can be obtained to understand or model the underlying cost curve.

The change in slope of the learning rate is very interesting as it can suggest a new regime of technology innovation, and a better understanding is needed for the drivers of it. If it is driven by external effects, then policy makers would like understand those impacts and where possible, reproduce those conditions.

However, the technology learning ecosystem as described above makes it difficult to disentangle “cause and effect” since there are both endogenous and exogenous factors, multiple interacting factors, and feedback mechanisms. A key question then becomes how to tease out generalized observations from a broader set of experience curves with known information about prices, component costs, market conditions, etc.

1.4 Previous work

Lesser-known alternatives to Wright’s Law are those of Goddard, who argues that annual production is the driver (reflecting economies-of-scale impacts) and combinations of these hypotheses (Nagy et al., 2013). A recent survey of experience curves can be found in Weiss et al. (2009) which quotes single-value learning rates for a wide range of end use technologies.

When using cost as a proxy for technology learning, it is important to understand other factors that could bias observed learning rates or create uncertainty. Economies of scale, research and development,

regulatory environments, and material and component prices all are believed to affect the cost of a given technology. Efforts have been made to distinguish the individual importance of these factors. Nemet (2006) used empirical data to create a model identifying the most important factors affecting the cost of PV and to what extent these factors are affected by genuine learning. Van Buskirk et al. (2014) explored the effect of appliance standards on technology learning rates and found that in many cases the introduction and continuation of standards is directly related to an increase in the learning rate. Ferioli et al. (2009) investigated the limitations of experience curves when used for product-level technologies, arguing that component-level learning behaves more predictably and is the driver for product-level learning.

In this work we provide experience curves for several energy-related technologies (electronic ballasts, magnetic ballasts, compact fluorescent lighting (CFL), general service fluorescent lighting (GSFL), stationary fuel cells in Japan and California, and the installed price of residential solar PV). These product technologies were selected because each have had known deployment programs, and examining experience curves in this light might help to determine if they represent an outcome from this external effect.

The approach and methods for constructing experience curves are presented in Section 2. Experience curve results and learning rates are presented in Section 3. Here, as a partial step to disentangling experience curve slope changes, we overlay the introduction of deployment programs on experience curves to explore the potential connections between deployment programs and a change in the learning rate. The goal is to try to better understand the possible linkage between deployment programs and the shape of the experience curve using the above logic and based on empirical data. Discussion of the analysis results and conclusions are provided in Sections 4 and 5 respectively.

2. Methodology

A significant source of difficulty in developing experience curves is the limited and disparate data available. To support our development experience curves, we gathered as much data as available from both the open and semi-open literature. From the open literature, data sources included price and production-volume data from government sources (e.g., the U.S. Census Department and U.S. Energy Information Administration (EIA)), reports from national labs (e.g., LBNL and PNNL reports) and other open sources of market data. If data from the above sources were not available, we utilized other sources of data, including market and data from private companies in the form of consultant reports; we attempted to corroborate these data with other data whenever possible.

Based on the availability of data, both domestic and international data sources are drawn upon. For example, electronic ballast and GSFL data are drawn from the U.S. Census Department's Current Industrial Reports (CIR), which constitute a historical record going back to 1958 for a variety of consumer products and are regarded as a high quality data set. Since both electronic ballasts and GSFLs are from the U.S. market, we also present CFL for the North American market. International data from CFLs is challenging to compile since there are a wide number of countries and data sources, although learning rates have been quoted in Iwafune (2000) and have been compiled and analyzed in a separate report (Smith et al., 2015).

A data fitting for best fit approach was taken adopted from Smith et al. (2015), where best fit lines are calculated for various break points and evaluated for the lowest mean square error as well as statistical significance.

In some cases, cost reductions may be occurring with a changing product type or changing product performance. Ideally, cost data would be normalized to service provided, such as lumens for lighting products or capacity or other quality metrics for appliances. Correcting for this was beyond the scope of this work, but product service levels were checked in two cases -- electronic ballasts and GSFL -- and the

level of service for both products is confirmed not to have decreased over time (see Appendix 1 for details of this analysis). Thus the cost reduction from electronic ballasts is not due to the product's delivering less lighting service over time.

3. Data

Table 1 summarizes our derived experience for the technologies considered in this report. Figures 2(a) through 2(i) show learning rates and 95% confidence intervals for linear sections of the experience curve. Note that several segments of the experience curves in Table 1 have a flat learning curve ("LR ~ 0%") since the learning rate from the regression fit line in these cases is not significantly different from zero. All plots follow standard conventions for plotting experience curves, e.g., price per units vs. cumulative production units for lighting products or price per kW vs. cumulative MW of production for energy supply technologies. For each product or technology we provide background information and deployment program history and then discuss the sources of data and observed experience curves.

3.1 Electronic and Magnetic ballasts

Background and deployment history Ballasts provide voltage and current control for fluorescent lighting bulbs (or lamps). For example, ballasts provide the initial voltage to strike the lamp's plasma and subsequently limit the flow of current to the lamp.

Electronic ballasts in particular are considered a very high impact technology and were discussed at some length in the National Academy of Sciences "Was it Worth It?" study on the costs and benefits of public energy efficiency investments (NAS 2001). The study highlights the cost effectiveness of initial R&D investment of the DOE in the seven year period from 1977 – 1983. This was a multi-year effort led by LBNL to evaluate the technology, develop electronic ballast prototypes and testing standards with several small companies. This investment amounted to total of \$3.2 million dollars (\$8.5M in current dollars). At the time, large companies were highly resistant and were not pursuing the technology, perhaps due to

skepticism of the technology or risk aversion and institutional inertia. R&D investment and capital investment may have been other barriers.

This early technology R&D led to the demonstration of 20-30% energy savings over existing magnetic ballasts and furthermore enabled the prospect for better lighting control, automation and dimming capabilities. The NAS estimated net cost saving of \$15 billion on this initial investment based on an assumption of a five-year market pull-in with the R&D investment versus the case of not making that investment. However, the NAS study does not examine the full range of deployment programs and their impacts beyond the first seven years of R&D investment.

This initial technology demonstration in the early 1980s is thought to have led large companies to make R&D and capital investments by the mid to late 1980s with resultant innovation in performance, cost reduction, and product envelope. Electronic ballasts began to penetrate the market in 1988 and increased in market share rapidly starting in the early 1990s, reaching about 72% of the market by 2005 and almost 100% in 2010. State standards for ballasts (either magnetic or electronic) were introduced in 1983 in California but the initial standards could be met with magnetic ballasts. Other state standards followed in several other states in the late 1980s. The first federal standards for lighting ballasts was introduced in 1990 and revised in 1993, 1995, 2000, and 2011.

Rebate programs and standards were key factors that encouraged greater adoption of electronic ballasts. The biggest breakthrough came when electronic ballasts were included in California's Title 24 building energy efficiency standards. Other deployment programs included the following: electric utility demand-side management programs, the ENERGY STAR[®] programs, federal energy management programs, and the American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) voluntary building code IES 90.1-1999.

In the 1990s, there was a wide range of utility incentive programs for electronic ballasts, totaling \$719 million and representing 13% of total energy efficiency program spending in 1994 and 1995 (Busch et al.,

2000). Other factors in 1980s and 1990s may have led to the greater acceptance of electronic ballasts e.g., private industry activities, greater acceptance of electronic components in general, and the concomitant cost reduction of electronics manufacturing overall.

Data and experience curves Data for electronic ballasts was drawn from the U.S. Census Department's Current Industrial Reports (CIR) from 1986-2005 and thus represents a high confidence experience curve. We plotted the cost per unit versus cumulative shipments. The experience curve exhibits piecewise-linear behavior with an initial learning rate of 8% from 1986 to 1992 and then a higher learning rate after that to 24%. Note that an earlier reference by Weiss (2009) quotes a learning rate of 11% for the years 1986-1997, which is the learning rate over these years for the CIR dataset, and Koomey et al. (1995) estimated an electronic ballast learning rate of 10%, which is also consistent with the CIR dataset for this timeframe.

Experience curve data for magnetic ballasts was drawn from Iwafune (2000), based on data from the U.S. Census Department. Again, there is a shift in the observed learning rate from 16% prior to 1990 to 39% after 1990. Note also the market price increased in 1990 due to shift in the magnetic ballast market to almost 100% efficient ballasts in 1990 from 37% market share in 1989. In this case and in other technology cases, state standards preceded the federal standard and it is possible that these state standards "primed" the industry for product redesign and readiness for more energy efficient products at the national level. The general dynamic here is that as state standards are implemented in successive states, manufacturers can expect that similar standards will be enacted at the national level and therefore their product development activities and technological progress are impacted. In this particular case, state standards were implemented for ballasts in California in 1983, seven years before the federal standard, and state standards in New York, Massachusetts, Connecticut, and Florida followed from 1986 to 1989.

The temporal difference in the discontinuities for magnetic and electronic ballasts (1990 versus 1993) appears to be related to the market shares of ballast technologies over time and the history of the energy

efficiency standards. Magnetic ballasts were the dominant technology in the domestically-produced market until the early 1990s and electronic ballasts did not achieve 1/3 of the domestically-produced ballast market until 1993. The discontinuity in magnetic ballast learning rate corresponds to the federal energy efficiency standard for ballasts that went into effect in 1990. This market data suggests that the increase in learning rate for electronic ballasts did not occur until higher volumes were achieved in the early 1990s and thus the discontinuity in learning rate occurred later than that seen in magnetic ballasts.

3.3 General Service Fluorescent Lighting (GSFL)

Background and deployment history The Department of Energy (DOE) has regulated the energy efficiency level of general service fluorescent lamps (GSFLs) since 1994. GSFLs are fluorescent tubes with pins at one or both ends for installation. These lamps are generally installed in ceilings.¹ GSFLs are distinct products as they represent lamps or fluorescent tubes but are part of a system insofar as a fluorescent tube lighting unit comprises both a bulb and ballast.

Data and experience curves GSFL data is drawn from U.S. Census Department's Current Industrial Reports (CIR) from 1960-1994. Three linear regimes are observed in the experience curve: a 21% learning rate from 1960 to 1968, virtually flat learning rate from 1969 to 1985, and then a 42% learning rate from 1985 to 1994.

The first discontinuity in 1968-1970 appears to be due to market consolidation and greater pricing power starting in the mid-1960s after a period with a much greater number of market participants and more intense competition. Waymouth (1989) notes that a period of industrial consolidation and technological quiescence occurred from around 1966 into the 1980s after a period of explosive technological progress prior to this from 1955 to 1965 (W-halogen, Metal halide, hi-power fluorescent, etc.). This period of consolidation corresponds reasonably well with the flat prices in GSFL lighting described in the paper from ~1969 to 1985.

¹ http://www1.eere.energy.gov/buildings/appliance_standards/product.aspx/productid/70, accessed 3 April 2015.

The first GSFL standard was not until 1994, but Figure 2(c) also shows state and federal ballast standards and DOE R&D investment in electronic ballasts from 1977 to 1983 as discussed in Section 3.1. The discontinuity in the mid 1980s is correlated to this onset of state and federal standards in the ballast component of GSFLs which necessitated more energy efficient lighting and greater technological innovation. Lamp "service level" as a function of time is also confirmed to not have decreased on a per unit basis over time. If this were the case, decreasing cost could simply be due to lower service levels.

3.4 CFLs

Background and deployment history Many deployment programs as well as exogenous events correlate to the sustained downturn seen in the experience curves below. Deployment programs include utility incentive and rebate programs, ENERGY STAR specifications and labeling, and U.S. DOE-led technology procurement programs which led to the development of new "sub-CFLs". Exogenous factors included the California electricity crisis of 2001 which triggered demand for efficient products, and market competition from a shift to production in low-income regions such as China (Weiss, 2008).

Data and experience curves A brief description of the CFL experience curve is provided here, with a more extensive analysis and discussion found in Smith et al. (2015). Cost data was collected from a variety of academic journal articles and industry reports (PNNL (2006), CPUC (The Cadmus Group, Inc., 2010), Southern California Edison (Itron, Inc., 2008), and ENERGY STAR (Bickel, 2010)), and all price data were converted to 2004 USD units using Bureau of Labor Statistics Consumer Price Index and currency conversion records reported by the U.S. Federal Reserve System. Here, only North American data is shown for CFLs since the ballast and GSFL experience curve data in this report is also for the U.S. market. Smith et al. (2015) discusses the international data and arrives at similar breaks in the experience curve.

The CFL experience curve, shown in Figure 2(d), demonstrates a somewhat surprising behavior. There is a change in the learning rate in about 1998 with a learning rate of 21% observed prior to 1998 and a rate

of 78% after 1998. Several key deployment-related factors discussed above are highlighted in Figure 2(d). There is also a substantial learning rate change after 2005, where the curve essentially flattens out. It is possible that this was due to market adoption saturation with costs driven to the minimal level.

Calculated learning rates for 1990-1998 align with findings in both Iwafune (2000) and Weiss (2006). Significant downturn during steady implementation of standards and programs has been seen in appliances, as previously discussed (Van Buskirk et al., 2015). An extensive discussion of deployment programs and linkages to the learning rate are provided in Smith et al. (2015).

For the four lighting-related technologies (electronic ballast, magnetic ballast, GSFL, and fluorescent lighting) there is typically a cost decline while the learning rate increases and a general correlation of deployment programs and learning rate increases. In only one case (magnetic ballasts from 1990 forward) is there a noticeable cost increase followed by a learning rate increase. This behavior could be due to higher initial production costs to meet the 1990 energy efficiency standard and market pricing power since the market for magnetic ballasts at that time was dominated by two firms (NAS 2000).

3.5 Stationary Fuel Cell Systems

Background and deployment history The U.S. Department of Energy (U.S. DOE) has historically invested in fuel cell technology development and deployment of FC systems (roughly \$95 million in fiscal year 2015) with recent reported success in the material handling and backup power segments and there is continued support from the federal government with a 30% federal tax credits for stationary FC power systems.² At the state level, there are various state incentive programs, for example the Self-Generation Incentive Program in California (SGIP).³ The SGIP offers incentives for on-site power and combined heat and power (CHP) generation including fuel cell systems with incentives declining by 10% annually and currently at \$1650/kW for fuel cell systems⁴. Thus, post incentive cost can be about half of

² <http://energy.gov/savings/business-energy-investment-tax-credit-itc>, accessed 10 March 2015.

³ <http://www.cpuc.ca.gov/PUC/energy/DistGen/sgip/>, accessed 10 March 2015.

⁴ <http://www.pge.com/en/mybusiness/save/solar/sgip.page>, accessed 1 April 2015.

the pre-incentive price, and the decline in incentive level may counteract cost reductions at the production level. Note also that over time, greater performance monitoring and reporting requirements for the SGIP program have been set and are possible contributing factors that could increase system prices.

The Japan micro-CHP program (also known as “Ene-farm”) supports small residential power and CHP units (0.7-1kW). The program began in 2004 and was commercialized starting in 2009 with generous rebates per unit decreasing over time (\$12,000 per unit in 2009 to \$3330 in 2014). For this period, most all fuel cell systems are polymer electrolyte membrane fuel cells (PEM FC) as Toshiba and Panasonic dominated the market through 2014 and both produced PEM FC systems. The Japanese government has set a goal of achieving \$5000/unit price in 2030, and market adoption targets of 1.4 million units in 2020 and 5.3 million units in 2030. Joint development is organized by a related organization in Japan, the Advanced Co-generation and Energy Utilization Center Japan that reports to the Ministry of Economy, Trade and Industry. Under this arrangement, joint development is conducted by city gas companies, LPG companies and the industrial partners including Toshiba Fuel Cell Power Systems, Aisin Seiki, Panasonic, and JX Nippon Oil and Energy (Kasuh, 2013).

Data and experience curves Data sources for micro-CHP in Japan are from trade show and technical conference presentations and publically available market reports. Data for California fuel cell (FC) costs are drawn from the California Self-Generation Incentive Program (SGIP). Note that data from California do not strictly constitute a domestic or international experience curve, but California still represents about 50% of the fuel cell market in the U.S. and is one of the few U.S. databases with price information.

The nominal learning rates for SOFC, PAFC, and MCFC, respectively, are not significantly different from zero in all three technologies. The market in California is typically for commercial power and CHP systems with system powers from about 200kW and higher.

Japan micro CHP had a learning rate of 18% from 2005 to 2014, as shown in Figure 2(e), but the California SGIP has not shown much cost reduction in recent years. The Japan market has a more

competitive market environment, more favorable market conditions (e.g. much higher price of grid electricity), and unlike the California and U.S. market, has established specified market adoption targets in units per year for 2020 and 2030 mandated by the Japanese government. An extensive discussion of fuel cell learning rates in Japan and California and micro-CHP cost reduction in Japan are provided in Wei et al. (2017).

3.6 Residential Solar PV (Installed)

Background and deployment history Two major revisions of the German feed-in tariff (FIT) law were introduced in 2000 and 2004. The 2000 revision provided fixed rates (\$/kW) over fixed periods, e.g., 20 years from the start of operation of each new qualifying plant. The 2004 revision also provided the following: RPS like targets for renewable energy (these targets committed Germany to increase the share of renewable energy in the country's total electricity supply to 12.5% by 2010, and to at least 20% by 2020); higher feed-in tariffs for solar installations; and improved legal status of renewable energy power plants. The German Renewable Energy Act of 2000 is estimated to have spent more than \$140 billion on the program with guaranteed returns to farmer and homeowners and other commercial cooperative willing to install solar PV, wind turbines and other renewable sources of energy.⁵

In the U.S., the solar Investment Tax Credit (ITC) is the most important national deployment in the U.S. The ITC provides a 30% tax credit for solar systems on residential and commercial properties⁶ and was established in 2006. Many states have additional incentive programs. For example, the California Solar Initiative (CSI) is the solar rebate program in California for investor-owned utility customers and is

⁵ Justin Gillis, Sun and Wind Alter Global Landscape, Leaving Utilities Behind, New York Times, September 13, 2014.

⁶ <http://www.seia.org/policy/finance-tax/solar-investment-tax-credit>, accessed 2 April 2015.

providing \$2.1 billion to businesses, nonprofit organizations, public agencies and homeowners who adopt solar technologies⁷.

Data and experience curves Experience curves are typically presented for *module* costs for solar PV with a median historical learning rate of 20% observed over several decades (IPCC, 2011). Data sources for the installed price of PV are taken from recent “Tracking the Sun” reports by LBNL, a Germany/U.S. installed price study also from LBNL (Seel, 2014), and various market reports on the size of the German and U.S. residential solar PV market.

Plotting this data, as shown in Figure 2(g), we observe a 33% learning rate from 2006-2011 in Germany for the cost of installed residential PV and a learning rate of 20% from 2009-2011 in the United States. A downward knee is seen in both countries.

We assume as in Seel (2014) that the module cost is virtually identical in the two locations. International market production of solar PV has been a major factor in reducing solar module costs. Seel et al. highlights three key areas for Germany to U.S. cost differences, all of which are non-module costs: (1) overhead, profit and other residual costs, (2) customer acquisition and system design, and (3) lower installation costs among other costs. Overall, about 30% of these cost differences are driven by deployment-related costs such as customer acquisition costs, permitting fees, and sales taxes. In particular, the feed-in tariff program in Germany was a national program that greatly increased visibility and attractiveness of residential solar PV installation and it is possible that this resulted in lower customer acquisition costs in Germany.

The importance of non-module costs such as installation and permitting is underscored in Table 2. For small residential systems (installed capacity less than or equal to 10kW), non-module costs (or balance of plant) increased to almost 90% of total installed price for systems less than 10kW from 59% fifteen years

⁷ <https://energycenter.org/programs/california-solar-initiative>, accessed 2 April 2015.

ago⁸) and thus, costs such as inverter costs, installation and other soft costs are more important than module costs in driving the overall installed price of solar PV.

3.9 Other Technologies and Other Studies

Preliminary learning rates were also found for two additional technologies: LED lighting and Li-ion batteries (Appendix 2). However the experience curve data for these two technologies were too sparse to draw any conclusions regarding learning rates, changes in the slope of the experience curve or any correlation to deployment programs.

In the course of study, a wide range of programs were considered for inclusion with a focus on those with known, documented experience curves. We highlight two examples here for comparison purposes.

In both Switzerland and Sweden in the 1980s and 1990s, there were many deployment programs. In particular there was a large scale Energy Program starting in 1990 in Switzerland with heat pump promotions, installation handbooks, and subsidies. Throughout this time period and into 2004, no downward kink was seen in the price of heat pump system components with a fairly steady learning rate of 35% (Weiss et al., 2008). However, Switzerland is a relatively small market and the price of components and systems is confounded with imported components.

Van Buskirk et al. (2014) perform a retrospective investigation of multi-decade trends in price and life-cycle cost (LCC) for home appliances in periods with and without energy efficiency (EE) standards and labeling policies. They find the introduction and updating of appliance standards is not associated with a long-term increase in purchase price; rather, quality-adjusted prices undergo a continued or accelerated long-term decline. In addition, long term trends in appliance LCCs—which include operating costs—consistently show an accelerated long term decline with EE policies. Their results suggest that “EE policies may be associated with other forces at play, such as innovation and learning-by-doing in appliance production and design, that can affect long term trends in quality-adjusted prices and LCCs.”

⁸ <http://emp.lbl.gov/sites/all/files/lbnl-6350e.pdf> Tracking the Sun VI, page 17.

Similarly, a recent report on U.S appliance standards from 2001-2011 has shown that several standard revisions have led to an increase in quality and either a modest effect on prices or a decrease in prices (Houde and Spurlock, 2015).

4. Results and Discussion

A key goal of this work is to view whether a downward bend exists in the experience curve and whether the knee can be attributed to endogenous or exogenous factors. To that end, we have constructed experience curves for several energy-related technologies with a history of government supported deployment programs. Similar to other recent studies, we observe a correlation of deployment programs with a shift to a faster learning rate, in particular for electronic and magnetic ballasts, CFLs, GSFLs, and the installed price of residential solar PV. Limited data exists for many products, partly an issue of trying to find costs for system components versus systems e.g., Li-ion automotive battery costs vs. the cost of vehicles, and also because of the relatively recent introduction of some technologies (e.g., LED lamps and Li-ion batteries).

Downward bending experience curves are found in 5 of the 6 energy technologies studied here (electronic ballasts, magnetic ballasts, compact fluorescent lighting, general service fluorescent lighting, and the installed price of solar PV). To our knowledge, this is the first paper to present a set of non-constant, downward sloping experience curves energy-related technologies on both the demand and supply side. Several cases utilize U.S. government-issued cost and shipment data sets (electronic ballasts, magnetic ballasts, and GSFL), and thus we have high confidence in their validity.

The work by Van Buskirk et al. (2014) outlined an intriguing finding on the linkage of federal appliance standards and learning rates, namely that the introduction and updating of appliance standards consistently show an accelerated long term decline in appliance life-cycle costs (which include operating costs). With a focus on one program type (standards) and one sector (appliances), Van Buskirk's findings are not sufficient to confirm that these linkages and shapes of learning curves apply in energy-related

technologies and whether they do so broadly. The present work effectively doubles the number of products and technologies from those that are analyzed in Van Buskirk. Additionally, our analysis provides further confirmation of the linkage between publically sponsored deployment programs and the change of slope in empirically observed experience curves. Thus, this work further broadens and expands the set of technologies and deployment programs from that considered in Van Buskirk, and thus opens the door for future study on the role of deployment programs and their impacts on technological change and the viability of identifying these changes in learning rates.

In many cases we are updating experience curves for technologies that have been reported in the past with more recent data, which underscores the need for regular periodic updates to ascertain changes in the learning rate. For example, electronic ballasts had an earlier reported learning rate of 10% (Weiss, 2009) but we find a much higher learning rate starting in the early 1990s. Data for more current years may be informative for some experience curves (e.g., GSFL), but is not necessary to demonstrate the changes in learning rate that are observed in this paper. For example, the learning rates in Figures 2(a), 2(b), and 2(c) are discrete piecewise-linear curves, and later data points would not change the dependencies or conclusions described in the paper.

For several technologies, various time periods have learning rates that are nearly zero, for example GSFLs from 1969 to 1985 and SOFC fuel cells in California from 2007 to 2015. This can arise from several possible reasons. Firstly, actual reductions in manufacturing and production costs may not be reflected in externally observable prices. As noted in Figure 1 (point A to point B), one example of this is in the situation where a technology provider may have pricing power from being a monopolist or near monopolist and can continue to charge higher prices than would exist in a market with more direct competition. This can also occur in some markets where there are attractive government subsidies and/or incentives, and since technology providers are able to charge a pre-subsidy or pre-incentive price that would otherwise be higher than a customer's willingness to pay, the subsidies and incentives can act as a price-support for the technology. Secondly, some technologies may reach a certain state of stasis where

the rate of learning slows down or flattens out over time either due to reaching a state of technological maturity (e.g, reaching physical limits such as thermodynamic efficiency) and/or a state where the technology providers are not actively investing in technology R&D, or both. In some cases, the learning rate may be negative over certain time periods (i.e., normalized cost increases) and that may be driven by other technological and non-technological factors. The nuclear industry, for example had rising costs from 1972 to 1996 in the U.S. due to high technological complexity, lack of standardization, and the regulatory environment for the nuclear industry, and quoting a learning rate in this case could be misleading (Grubler 2010).

Other experience curves with ongoing deployment programs do not have change in slope, for example, the case of Swiss heat pumps (HP) and stationary fuel cells (FC) in California. In the case of Swiss HP, the Swiss market for HP production is relatively small and the cost of HP components is confounded with imported components. In the case of California FC systems, a fully competitive market is still lacking across the range of commercial system sizes, and overall unit volumes are still low (see Wei et al. (2017) for more details).

Relative to Figure 1, where the initial downward bend in the experience curve is attributed to new product shakeout, GSFL costs experienced a long flat period in 1970s followed by a downward bend in a mature industry that had been in existence for over 20 years. Thus the change in learning rate was evidently not from a market shakeout in a new technology, but from other forces, which we attribute to technological innovation arising in part from a new imperative on energy efficient technology and energy efficient ballast technology in particular, and from the expectation of the introduction of standards for GSFL.

A complimentary approach to the one adopted here would plot the “service provided” versus cumulative production volume where service provided might be lighting service for lighting products or heating service for heating products, or perhaps life-cycle cost as in Van Buskirk et al (2014). The slopes of the experience curves here are not explicitly normalized to product performance; however in the case of

electronic ballasts and GSFLs, we have verified that the service output has not dropped over time. In other technologies, we adopt fairly standard product metrics such as price per kW for fuel cells and solar PV.

4.1 Directions for Further Work

Key unanswered questions include the quantification of sources of error and uncertainty, delineation of prices versus underlying costs; learning rates for domestic versus international markets; further development of the interplay of deployment programs and technological innovation, the interactions of component cost reductions and system costs or prices, and prediction of how a given technology's experience curve may unfold and evolve under various market, technology, and policy scenarios.. For example, the NiMH battery has been the primary battery for hybrid vehicles and there have been studies about hybrid vehicle cost reduction (e.g. Weiss et al., 2012); but to the authors' knowledge very little have been reported on the NiMH battery component cost. There may be difficulties in obtaining component level cost data that is not normally sold to the general consumer. Conversely one would expect that component cost reductions to lead to or dictate system cost reductions. This appears to be the case with GSFL, where the invention of alternative ballast and improved incumbent technology may have been one of the catalysts or perhaps the "impulse function" that increased the GSFL providers' interest in energy efficiency and applying the emerging technology to their base technology.

A better understanding of cost reduction drivers would be helpful (e.g., exogenous vs. endogenous; economies of scale vs. learning by doing vs. foreign competition, etc.) as well as factoring in the role of producer pricing and possible market power (Spurlock, 2013) and in general trying to gain greater certainty in the observed shifts in some of the curves.

Potential follow ups could be disaggregation of cost reduction into constituent costs and deeper study into some of the intriguing technology experience curves above such as GSFL, possibly with extensive stakeholder interviews. A deeper study into the classification of learning rates by technology "family"

would be informative. For example, do electrochemical technologies (e.g., batteries and fuel cells) have a lower learning rate in general than other technology families such as electronics-based technologies such as semiconductors and solar PV, and how might this vary across technology development phase (e.g., early vs. mid-commercialization vs. full-commercialization)?

Another important question for deployment programs is how analysts should model counterfactual scenarios of “no deployment programs”. Comparing technology roll-outs and policy targets between countries may provide insights as in the solar PV case of soft costs and customer acquisition costs or stationary fuel cell deployment programs.

For solar PV, there may also be a pricing effect, namely that over generous subsidies in Germany may have boosted prices to artificially high levels with reductions in price lagging actual reductions in supplier costs. This is a specific example where price-based experience curves can mask actual cost reductions and implied innovation. There are many general critiques of renewable energy and solar PV subsidies leading to much higher electricity prices,⁹ but the price-to-cost time lag effect should be an area for further study and better quantification.

5. Conclusions and Policy Implications

By updating and compiling experience curves of several energy technologies we have revealed non-linear behavior in technologies that have previously been viewed as having a lower learning rate (ballasts, CFLs) and observe non-linear experience curves in many technologies. Thus it is important to revisit LCs with some regularity since very dynamic and single value learning rates for a given technology cannot be assumed for the future.

⁹ Some reports are critical of the German government’s approach to renewable energy subsidies and report that the Germany subsidy program has greatly increased the cost of electricity (e.g. Smil, V. (2012), "A skeptic looks at alternative energy," *Spectrum, IEEE* , vol.49, no.7, pp.46,52, July 2012 doi: 10.1109/MSPEC.2012.6221082).

We have presented empirical experience curves for six technologies (electronic ballasts, magnetic ballasts, GSFL, CFLs, fuel cell systems, and the installed price of solar PV). Five of the six have curves have observed bends downward in the shape of the experience curve (electronic ballasts, magnetic ballasts, GSFL, CFLs, installed price of solar PV) and correlations to deployment programs are observed in each of these technologies.

This analysis is not suggesting a causal relationship at this point in time, but highlighting a striking correlation between the implementation of deployment programs and a change in slope of the experience curve. The work is thus an initial step in highlighting the direct linkage between government deployment programs and potential increases in the learning rate. We also described a prescriptive data gathering approach for constructing experience curves and overlaying upon them deployment program activities. This analysis can be applied to future technology-driven deployments by providing insight to the potential benefits of federal and state deployment investments.

Since a downward change in the slope of the price-based learning curve is a desirable outcome from a consumer perspective, federal and state government policy makers can more carefully evaluate the cost evolution and performance features for energy-related technologies. To the extent that novel or unexplored technology features, product applications, or supporting cost reductions have not been pursued, or where the industrial suppliers in question have no incentive to pursue these, policy makers should consider the role that deployment programs can play in stimulating new thinking, incentivizing new product designs, or in improving metrics such as the performance-to-cost ratio. For example, neither energy efficiency nor efficient ballast design was a priority in the lighting industry during the late 1960s and 1970s. Focusing on energy efficiency deployment programs in lighting ballasts and GSFLs starting in the mid-1980s are strongly correlated to sharp gains in the learning rate for fluorescent lighting after 15 years of near-zero learning rate.

Experience curves are driven by a complex interaction of factors of which deployment programs are only one. Greater adoption of a technology, for example, can be spurred by deployment programs as well as other exogenous factors, fuel costs, increased technology acceptance, and improvements in product performance. Nonetheless, these findings of non-constant, downward bending learning curves across a set energy technologies are noteworthy, highlighted here for the first time, and supported by high-quality data sets. Together with the earlier work by Van Buskirk et al. (2014), this work suggests that deployment programs have a role to play in fostering cost reduction forces such as technology innovation and learning-by-doing that can lead to faster learning rates.

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Appendix 1 – Service Levels in Electronic Ballasts and General Service Fluorescent Lighting

The general question that is addressed in this section is the following: is a downward bend in the slope of an experience curve due to a change in the learning rate or is it due to a change in service level, i.e., to a lower level of service per unit and thus a lower cost per unit? The experience curves for electronic ballasts and general service fluorescent lighting (GSFL) presented in the main text draw from the U.S. Census Department's Current Industrial Reports (CIR) and represent the average value (price) per unit of each product. This average includes a variety of product types, and the characteristics of those product types may change over time. From the Census data, we have data on the distribution of units by product type for each year, but CIR do not provide the exact distribution of power and lumens for each product type, which therefore must be estimated or inferred.

A full treatment of this problem would break out electronic ballast and GSFL by each product class, e.g. high output GSFL lamps vs. GSFL 48" fluorescent lamps vs. Slimline lamps, etc., and/or normalize each experience curve to service provided, e.g., how has the cost per thousand lumens evolved over cumulative production volume. The experience curve could thus be plotted more precisely as cumulative units on the x-axis vs. some metric of service on the y-axis such as lumens per unit, or conversely, cumulative power shipped in MW on the x-axis vs. some metric of service on the y-axis. In practice this is more difficult than plotting the average cost versus cumulative units shipped for two reasons: (1) the product types in the CIR data have some changes over time and (2) the level of service by product type is neither recorded nor defined. Here, we simply provide data showing that the inferred service levels per unit for electronic ballasts and GSFL lamps have not decreased over time (and may in fact have increased over time), and thus the downward bends in the experience curve for these products is due to a change in the learning rate and not due to a shift to lower service levels.

For lighting products we take “lumens per unit product¹⁰” as an initial metric for service level, where lumens is a metric for the amount of light that is usable by the human vision system. We make the following assumptions in this analysis: (1) the luminous efficacy (LE, defined as lumens per watt) for fluorescent lighting has increased by an average annual rate of 1.5% per year¹¹; (2) the luminous efficacy is approximately the same for various types of fluorescent lighting; (3) within a given product class and where the distribution of product wattages is not known, e.g., for high output fluorescent lamps, and Slimline lamps, we assume that the average service level in lumens per unit does not drop over time; (4) we assume that lighting quality from GSFL or electronic ballasts in general increases over time in terms of resultant product flicker, lifetime, lighting color, etc., although the quantification of each of these metrics was beyond the scope of this work. Assumption 1 is the average rate of increase in LE over this time period from two references. Assumption 2 is perhaps the most questionable and variable, but more detailed product level cataloging by product type and year was beyond the scope of this work. Assumption 3 is reasonable insofar as for a given product type such as Slimline or High Output that form recognizable market segments, manufacturers would probably not reduce average service levels over time.

A1.1 Electronic Ballasts

The study period for this product is 1992 to 2004, when we observe an apparent increase in the learning rate for electronic ballasts. Table A1.1 has data from CIR for market share and product types, while luminous efficacy was assumed as above and wattages for each product type are either estimated from the CIR data or estimated based on the above assumptions.

¹⁰ For electronic ballasts, lumens per unit refer to the lumens level of the accompanying fluorescent lamp that the ballast supports.

¹¹ Sources: (1) http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl/ssl_mypp2013_web.pdf, accessed 13 March 2014; and (2) <http://blog.fairchildsemi.com/wp-content/uploads/2015/02/Fig.-1-Efficacy-and-Projections-of-Different-Light-Sources.png>, accessed 7 April 2015.

Table A1.1. Estimation of lumens per unit for electronic ballasts for 1992 and 2004.

	LE (lm/W)	Inferred Wattage/unit	Market Share	Approx. Lumens/unit
1992 Product Types				
<i>Less than 40W</i>		<i>31</i>	<i>90%</i>	<i>1498</i>
<i>High Output</i>		<i>141</i>	<i>10%</i>	<i>6900</i>
Assumed Luminous Efficacy	49			
Avg. lumens/ unit				2039
2004 Product Types				
<i>All 32W</i>		<i>32</i>	<i>79%</i>	<i>1897</i>
<i>All 59W</i>		<i>59</i>	<i>2%</i>	<i>3499</i>
<i>Not specified</i>		<i>30</i>	<i>3%</i>	<i>1779</i>
<i>High output</i>		<i>116</i>	<i>6%</i>	<i>6900</i>
<i>CFL 26W</i>		<i>26</i>	<i>8%</i>	<i>1542</i>
<i>CFL >26W</i>		<i>30</i>	<i>2%</i>	<i>1779</i>
Assumed Luminous Efficacy	59			
Avg. lumens/ unit				2199

From Table A1.1 the average lumen/unit in 2004 is slightly higher than 1992. Even assuming lumens per unit is approximately flat, other factors contributed to higher level of service over time. The 2004 CIR has ballast product types “supporting 3-4 lamps” (a product subset grouping of the 32W product type), whereas 1992 only mentions product types “supporting up to 2 lamps”, so the serviceable number of

lamps per ballast also evidently increased. Overall quality also improved from the early commercial electronic ballasts to those shipped in 2004.

A1.2 GSFL

GSFL Lamp service level in lumens per watt as a function of time is also confirmed to be non-decreasing on a per unit basis over time periods where the learning rate experiences a sharp increase. For illustration we consider the years 1970 and 1992. We present two approaches for quantifying the level of service in lumens per unit shipped in each year.

We define are two categories of general service fluorescent lamps: Recurring (Slimline, Circular, and High Output) and Other. The first analysis approach notes the relative shifts in product type shipments between the two years. Lamps in the Recurring Category have shifted to a greater fraction of high output lamps and a lower fraction of Slimline and Circular products, and thus on a per unit basis, service levels have increased. Meanwhile lamps in the Other category have shifted from about 80% of units in the "Above 40W" in 1970 to about 84% of units in the "Above 30W" in 1992. Note that the product types in the Other category have shifted in definition from having a 40W breakpoint in 1970 to a 30W breakpoint in 1992, implying that the distribution of power levels has moved downward by roughly 25%. This is consistent with the fact that with increasing luminous efficacy, the lamp power required to produce the same level of lumens is reduced. For analysis purposes, we assume that there were two distributions of power levels centered at P_1 , P_2 in 1970 (low and high power, respectively) and at $P_1 \times 75\%$ and $P_2 \times 75\%$ in 1992 with $P_1 > 40W$ and $P_2 < 40W$. With these assumptions, and for a wide range of reasonable P_1 and P_2 , service levels stayed flat or increased because there is an equal to greater increase in luminous efficacy over the same time frame, i.e. Lumens (= Lamp Power (down by about 25% from 1970 to 1992) $\times$ LE (Up by $\geq 25\%$ from 1970 to 1992) is flat to slightly higher.

A second heuristic approach of viewing this question is as follows: we assume that the lumens delivered by each lamp type in 1970 is a fixed value over the time period of interest, e.g., service levels, or

"brightness" for given products such as fluorescent tubes and circular lighting has not dropped on a per unit basis over time. Then the distribution of units by product type reported in the CIR is such that the average service delivered by lamp has remained flat over this time range (see Table A1.2). As before, lumens/unit is only one aspect of product service and performance. Over the two decades of this analysis, other aspects of product service such as product quality and flicker also improved.

Table A1.2. GSFL product types, % of shipped units in 1970 and 1992 and estimated average lumens/unit.

	LE (lm/W)	Inferred Wattage/unit	Market Share	Approx. Lumens/unit (held fixed)
1970 Product Types				
<i>Recurring</i>				
<i>Slimline</i>		68	17%	2400
<i>Circular</i>		57	3%	2000
<i>High Output > 80mA</i>		196	7%	6900
<i>Other, < 40W</i>		31	15%	1100
<i>Other, > 40W</i>		77	58%	2725
Assumed Luminous Efficacy	35			
Avg. lumens/ unit				2703
1992 Product Types				

<i>Recurring</i>				
<i>Slimline</i>		49	11%	2400
<i>Circular</i>		41	1%	2000
<i>High Output > 80mA</i>		141	6%	6900
<i>Other, < 30W</i>		23	13%	1100
<i>Other, > 30W</i>		56	69%	2725
Assumed Luminous Efficacy	49			
Avg. lumens/ unit				2700

Appendix 2 – Preliminary Learning Rates for LED lighting and Li-Ion Batteries

Background information, data, and some discussion are also provided for two additional technologies (LED lighting and Li-ion Batteries) in this Appendix. These are meant to be preliminary learning rates (Table A2.1) since that the experience curve data sets for these two technologies were not sufficient to draw any conclusions for this work.

A2.1 LED lighting

Background and deployment history The U.S. Department of Energy (DOE) has led multiple deployment programs for solid state lighting (LED) since 2006. These programs include: voluntary rigorous testing and evaluation of lighting products (CALiPER Program), maintenance of a public

database of industry lighting products and their performance (LED Lighting Facts), standards development, demonstration programs, numerous industry/stakeholder workshops on R&D status and priorities, and sponsorship of high profile international contests, including one for the A19 general service lamp. In addition, the DOE has partnerships for outreach and incentives with dozens of utilities, energy efficiency organizations and municipalities around the country. There are at least 35 state-level incentive programs for energy efficient lighting, mostly in the business and commercial sectors.¹²

Data and experience curve LED products span a very broad market from displays to automotive headlights to general lighting. Here, we focus on A19 general service lighting, i.e., 60W incandescent or CFL replacement lamps. Market sales are taken from the National Electrical Manufacturers Association (NEMA) quarterly reports for sales and utilize EIA data for prices¹³. There is limited data for A19 products, since these LED-based lamps were only introduced a few years ago. We compute a preliminary learning rate of 18%, which is consistent with a more detailed treatment by Gerke et al. (2014) using a “web-scraping” method of collecting a large sample of LED lamp prices from retail sites on the Internet.

A2.2 Li-ion batteries

Background and deployment history The U.S. DOE and the state of California have a long history of research, development and deployment of electric vehicles starting from the mid-1970s. . The Freedom Car and Fuel Partnership was established in 2002 with a focus on commercial, fuel cell, and Li-ion technology and passenger HEVs. From 2002-2013, federal R&D in energy storage increased from \$24.1 to \$157.9 million. In 2007, the Advanced Technology Vehicles Manufacturing (ATVM) was authorized to award up to \$25 billion in loans. The 2009 American Recovery and Re-investment Act (ARRA) federal stimulus invested \$2.4 billion for advanced battery manufacturing. In 2012, California’s Governor Jerry Brown announced a new ZEV mandate in California with the goal of 1.5 million ZEVs in

¹² <http://programs.dsireusa.org/system/program>, accessed 1 April 2015.

¹³ <http://www.nema.org/news/Pages/LED-A-line-Replacement-Lamps-Begin-Making-Inroads-into-the-Market.aspx>; <http://www.nema.org/news/Pages/Compact-Fluorescent-Lamp-Shipments-Continue-to-Lag.aspx>; <http://www.eia.gov/todayinenergy/detail.cfm?id=15471>, all accessed on 20 January 2015.

the state by 2025. At the consumer level, there is a federal tax credit of up to \$7500 for plug-in and battery vehicles, and various state incentives and rebates¹⁴.

Data and experience curve Price data for lithium-ion (Li-ion) automotive batteries utilized data from Canis (2010), Bloomberg, and Navigant.¹⁵ Global sales were taken from a report by the International Council on Clean Transportation (Mock, 2014). Cumulative sales in MWh were based upon global sales figures and the average kWh size for all plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV) vehicles sold on the global market. The data for cumulative sales and average kWh size is in principal available from automakers sales and annual report information, but for this work, we relied on reported sales and car battery capacities from the Internet¹⁶ to compute the total MWh in the global market.

A preliminary learning rate of 12% is estimated for Li-ion batteries. The observed learning rate is similar to modeled learning rate estimate of 10-15% from Kamath (2009). This learning rate compares favorably to an earlier learning rate reported for nickel-metal hydride (NiMH) batteries (LR= 9-10%) from Kalhammer (2007), but note that this reference also has very scant data on NiMH prices.

¹⁴ <http://driveclean.ca.gov/pev/Costs/Vehicles.php>, accessed 1 April 2015.

¹⁵ <http://about.bnef.com/summit/content/uploads/sites/3/2013/12/2013-04-23-BNEF-Summit-2013-keynote-presentation-Michael-Liebreich-BNEF-Chief-Executive.pdf>, accessed 7 October 2014;
<http://www.batterypoweronline.com/main/articles/the-lithium-ion-inflection-point/>, accessed 30 October 2014.

¹⁶ See for example, <http://evobsession.com/world-electrified-vehicle-sales-2013/>, accessed on 26 October, 2014.

Table 1. Summary of experience curve-derived learning rates with 95% confidence limits.

Table 2. Fraction of module costs vs non-module costs for residential PV (less than or equal to 10kW) from Barbose, et al. 2014.

Table 3. Summary of learning rates for U.S. appliances and transition years for life-cycle cost and quality-adjusted price (from Buskirk et al., 2014)

Table A2.1. Preliminary learning rates for LED lighting (A19 lamps) and Li-ion batteries.

Figure 1. Price-cost relations for a new product (from Boston Consulting Group (1968)

Figure 2. Observed learning rates for several energy-related technologies.

- (a) Electronic Ballasts
- (b) Magnetic Ballasts
- (c) General Service Fluorescent Lighting
- (d) Compact Fluorescent Lighting
- (e) Japanese Micro-CHP Fuel Cell Systems
- (f) Stationary Fuel Cell Systems in California
- (g) Installed price of residential solar PV

Figure A2.1. Observed learning rates for LED lighting and Li-ion batteries

- (a) LED lighting (A-lamps)
- (b) Li-ion Batteries

Product	Years	Learning Rate from this Work	Sources
Electronic Ballasts	1986-2005	8% $\pm$ 4% (U.S., 1986-1992) 24% $\pm$ 2% (U.S., 1993-2005)	U.S. Census Current Industrial Reports
Magnetic Ballasts	1981-1993	16% $\pm$ 5% (U.S., 1981-1989) 39% $\pm$ 28% (U.S., 1990-1993)	U.S. Census Current Industrial Reports
General Service Fluorescent Lighting	1960-1994	21% $\pm$ 3% (U.S., 1960-1968) ~0% at 1% $\pm$ 3% (U.S., 1969-1985) 42% $\pm$ 7% (U.S., 1986-1994)	U.S. Census Current Industrial Reports, via Iwafune (2000)
CFLs	1990-2007	21% $\pm$ 6% (N. America, 1990-1998) 78% $\pm$ 4% (N. America, 1999-2005) ~0% (N. America, 2006-2007)	PNNL, CPUC, Southern California Edison and ENERGY STAR
Stationary Fuel Cells	2001-2014	~0% at -1% $\pm$ 1% CA SOFC, 2007-2015) ~0% at 9% $\pm$ 9% (CA MCFC CHP, 2003-2014) ~0% at 4% $\pm$ 8% (CA PAFC CHP, 2001-2013) 18% $\pm$ 2% (Japan Micro CHP, 2005-2014)	California Self-generation incentive program Various market reports and technical conferences
Solar PV Installed Price	2002-2011	20% $\pm$ 12%(U.S., 2009-2011) 33% $\pm$ 8% (Germany, 2006-2011)	LBNL reports, various market reports

(PNNL = Pacific Northwest National Laboratory; CPUC = California Public Utilities Commission; NEMA = National Electrical Manufacturers Association; EIA = Energy Information Administration)

Cost component	1998	2012
Non-module costs	59%	87%
Module costs	41%	13%

Appliance	First Standard Year	Price Transition Year	Pre Transition LR, Price	Post Transition LR, Price	LCC Transition Year	Pre Transition LR, LCC	Post Transition LR, LCC
Refrigerators	1977	1995	44%	65%	1972	22%	58%
Clothes washers	1988	1987	27%	49%	1990	8%	56%
Room air conditioners	1979	1973	17%	41%	1976	10%	41%
Central air conditioners	1979	1974	5%	18%	1976	1%	23%