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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 and technology market forecasters is to estimate future technology costs and in particular the rate of cost reduction versus production volume. A related, critical question is what role should state and federal governments have in advancing energy efficient and renewable energy technologies? This work provides retrospective experience curves and learning rates for several energy-related technologies, each of which have a known history of federal and state deployment programs. We derive learning rates for eight technologies including energy efficient lighting technologies, stationary fuel cell systems, and residential solar photovoltaics, and provide an overview and timeline of historical deployment programs such as state and federal standards and state and national incentive programs for each technology. Piecewise linear regimes are observed in a range of technology experience curves, and public investments or 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 8 energy-related technologies presented here (electronic ballasts, magnetic ballasts, compact fluorescent lighting, general service fluorescent lighting, and the installed cost of solar PV). 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 highlights the impact of exogenous government sponsored deployment programs. This work can inform future policy investment direction and can shed light on market transformation and technology learning behavior.

1. Background and Motivation

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 it invest in research, development or deployment; how should it 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.

A first step to disentangling this question is constructing experience curves and deriving learning rates with as much empirically available evidence as possible. This approach allows us to compute learning rates, summarize data availability and trends, and overlay historical deployment programs upon compiled experience curves. With this approach of data collection and assemblage of historical deployment programs, we are able to develop experience curves, summarize changes in learning rates and provide interpretations for the role that government can play in implementing such programs.

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

$$C(t_2) = \text{cost at time } t_2 \text{ and } V(t_2) = \text{cumulative production volume at time } t_2$$
$$C(t_1) = \text{cost at time } t_1 \text{ and } V(t_1) = \text{cumulative production volume at time } t_1$$

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).

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. Canonical experience curves

Shifts-in-the-price (Boston Consulting Group, 1968) versus cumulative output is shown schematically in Figure 1 below. Experience curves are typically presented on a log-log plot, e.g., 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 (Price – Cost) 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 such as technological learning and innovation 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. Mechanisms for this are that new entrants may be attracted to a growing market with a few suppliers or perhaps patent protection has lapsed or new production facilities are opened abroad.

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) 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.
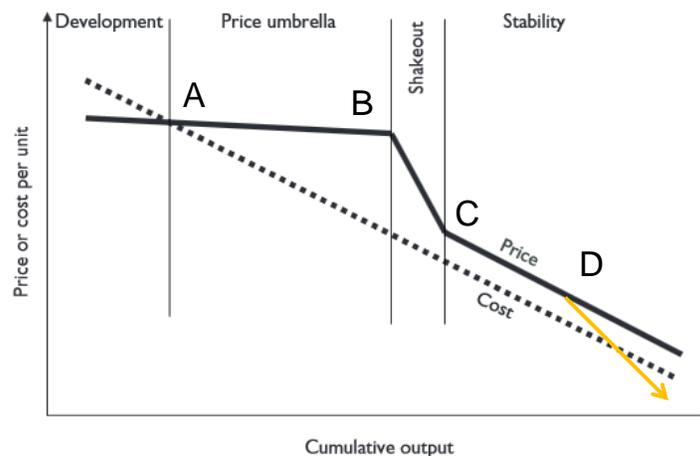

Figure 1. Price-cost relations for a new product (Boston Consulting Group, 1968)

The change in the slope of the price-production curve, the learning rate, is very interesting as it can suggest a new regime of technology innovation. A better understanding is needed for the drivers of such a change. If it is driven by external effects, then policy makers would like understand those impacts and reproduce those conditions where possible. In this work, we examine experience curves in the presence of deployment programs in order to help to determine if changing learning rates represent an outcome from this external effect. The product technologies described below were selected because each have had known deployment programs. For example, there are well defined and characterized deployment programs in ballasts and lighting as well as solar PV and fuel cells in California. We also consider an international case for fuel cell micro-CHP in Japan.

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 affecting the learning rate. A key question then becomes how to tease out generalized observations from a broad set of experience curves with known information about prices, component costs, market conditions, etc. Other key questions are the quantification of sources of error and uncertainty; geographic boundary conditions of domestic versus international experience curves; product boundary conditions e.g., system costs versus component costs; presence of constant vs. non-constant learning rates; and given an emerging technology, how might the experience curve unfold and evolve under various market, technology, and policy scenarios? We comment on each of these considerations in the discussion of empirically observed experience curves below, and from this discussion also highlight key areas for follow-up investigation.

1.3. 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. This interconnected set of market and technology factors can act to generate cost reduction, at times in reoccurring feedback loops. 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.

In addition to the discussed factors, there is the role of public policy programs which can encourage lower technology costs in various ways. 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, for example by increasing adoption and encouraging development of new or improved products. Deployment programs have been identified as key activity for emerging energy-related technologies is the pilot/early commercialization stage of the research, development and deployment chain. Here deployment is defined fairly broadly and can include incentive programs, state and federal standards, contests, state and federal procurement, information and education programs, public testing and performance databases, and so on.

Often-seen plots of cost versus time for a given technology do not include sales adoption or cumulative volume. Experience curves, which plot cost vs cumulative volume, are another useful depiction for such data. For a policy maker or supplier firm with a technology roadmap, a cost target by a certain date is typically defined, and an experience curve can be used to understand the mechanisms by which that target can be reached. For example, "moving down" the experience curve is achieved by increasing market adoption and through "learning-by-doing" improvements (e.g., improvements in the manufacturing process) or other technological improvements. Projecting forward with the historical learning rate will thereby set a market adoption target by a certain date and this will serve as guidance for setting incentives or other deployment programs for the policy maker. If the LR in this case is misestimated, investment to increase adoption may be misallocated, e.g., if the actual LR is slower, target investment may be inadequate. Thus extrapolation and interpretation of the existing experience curve has a large impact on achieving the cost vs. time target. On the other hand, historical experience curves can be used looking back to ask the question of whether we can relate the LC retrospectively to deployment programs and other factors.

1.4. Previous work

An alternative to Wright's Law is Moore's Law, which suggests that technology improves exponentially with time as opposed to cumulative production. In cases where production increases exponentially with time, the two are the same. Lesser-known alternatives to these laws 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 or price 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, light emitting diode (LED) lamps, and lithium-ion batteries for plug-in electric vehicles). 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. Approach

A significant source of difficulty in developing experience curves is the limited and disparate data available. To support our development of 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 data from private companies in the form of consultant reports. We attempted to corroborate these data with other data whenever possible.

In this work, the boundary conditions of market and technological maturity are primarily that the technologies are in early commercialization to full commercialization. Based on the availability of data, both domestic and international data sources are drawn upon. For example, the U.S. Census Department's Current Industrial Reports (CIR) constitute a historical record going back to 1958 for a variety of consumer products that is regarded as a high quality data set. Electronic ballasts and GSFL data are drawn from this 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 segmented regression data fitting approach was adopted from Smith et al. (2015), where a regression process finds best fit lines with and without break points, determines break point locations and significance based on lowest mean square error and significance testing, and assesses appropriateness of adding break points using an information criterion.

For lighting, a per-unit basis is used for cost and volume values. Alternative metrics such as service provided (e.g. lumens for usable light) were examined for electronic ballasts and general service fluorescent lighting (GSFL), but this disaggregation can be difficult to split out since data is not always paired with product specifications, and product types change over time. Ideally, the cost should be normalized to service provided, e.g., lumens (usable light) for lighting products, or capacity or other quality metrics for appliances. Product performance can improve in some cases, for example with larger capacities or more feature sets, and not accounting for this in cost analysis may skew results. 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. Similarly, the average levels of lumens for GSFL have not dropped over time, so the observed price reduction is not due to lower levels of service.

3. Results

Table 1 summarizes our derived learning rates for the technologies considered in this report. Figures 2(a) through 2(g) show learning rates for linear sections of the experience curve with deployment programs superimposed on the curves. For each product or technology, we discuss the sources of data and observed results. Detailed background information is provided for electronic ballasts since ballasts are a key component in both GSFLs and CFLs.

Table 1. Summary of experience curve-derived learning rates.

Product	Years	Learning Rate from this Work	Sources
Electronic Ballasts	1986-2005	8% (U.S.) 1986~1991 23% (U.S) 1992-2005	U.S. Census Current Industrial Reports
Stationary Fuel Cells	2001-2014	~0%, California 12%, Japan Micro CHP 2009-2014	California Self-generation incentive program Various market reports and technical conferences
Compact Fluorescent Lighting (CFL)	1990-1998 1999-2005 2006-2007	22% (N. America) 79% (N. America) ~0% (N. America)	PNNL, CPUC, Southern California Edison and ENERGY STAR
General Service Fluorescent Lighting (GSFL)	1960-1994	19% (U.S.) 1960-68 ~0% (U.S.) 1969-1985 40% (U.S.) 1986-1994	U.S. Census Current Industrial Reports
Light Emitting Diode (LED)	2011-2014	18% (U.S.)	NEMA, EIA
Li-ion Batteries	2011-2014	12% (Global)	Navigant, various market reports
Solar Photovoltaic (PV) Installed Costs	2008-2014	22% (U.S.) 31% (Germany) in recent years	LBNL reports, various market reports

(PNNL = Pacific Northwest National Laboratory; CPUC = California Public Utilities Commission; NEMA = National Electrical Manufacturers Association; EIA = Energy Information Administration)
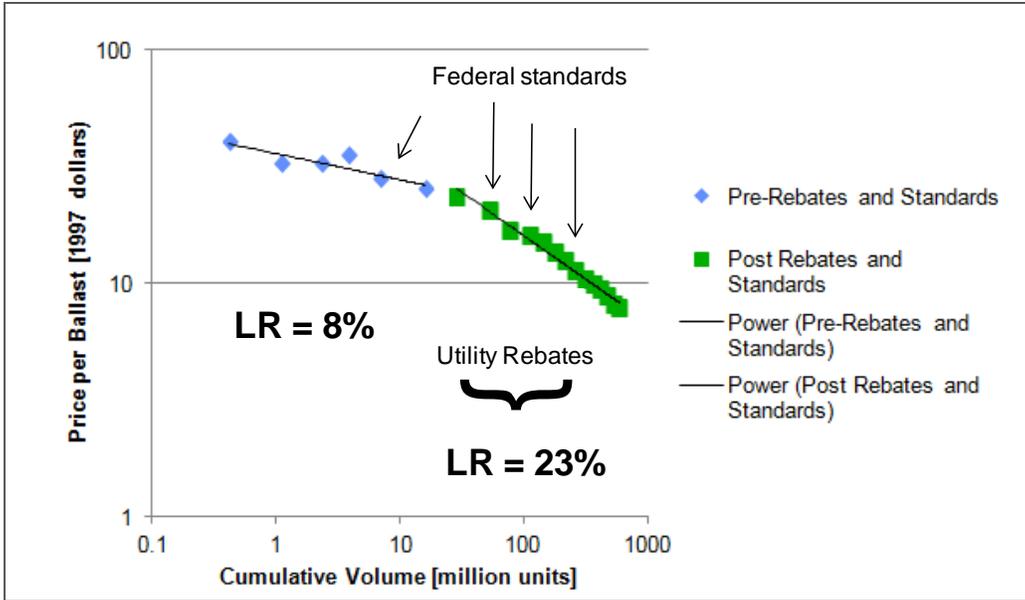
(a) Electronic Ballasts
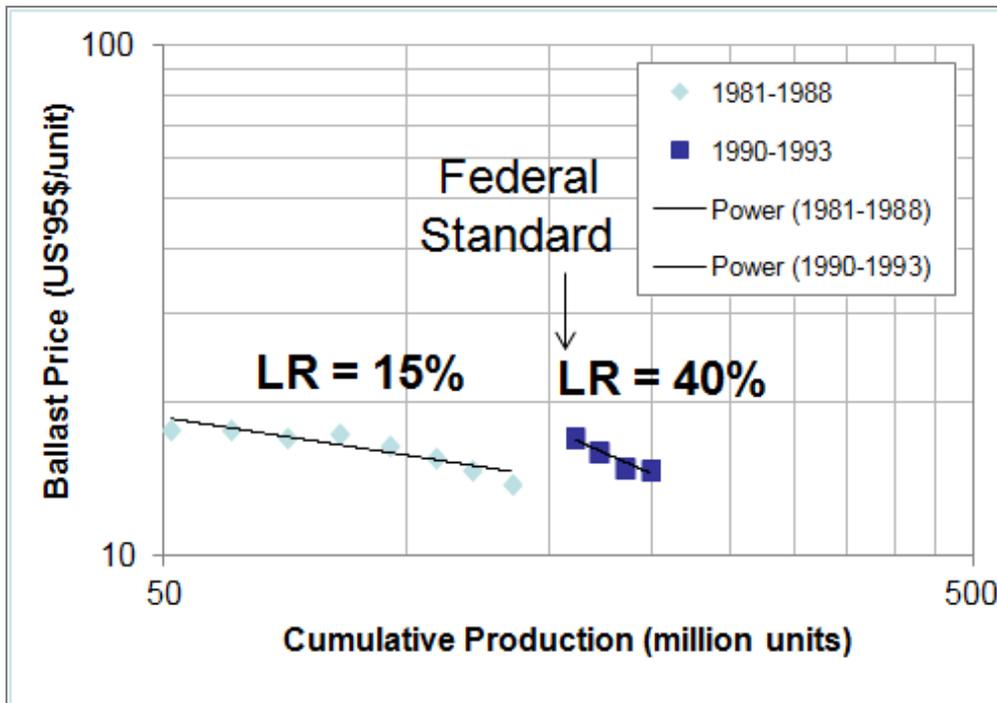
(b) Magnetic Ballasts
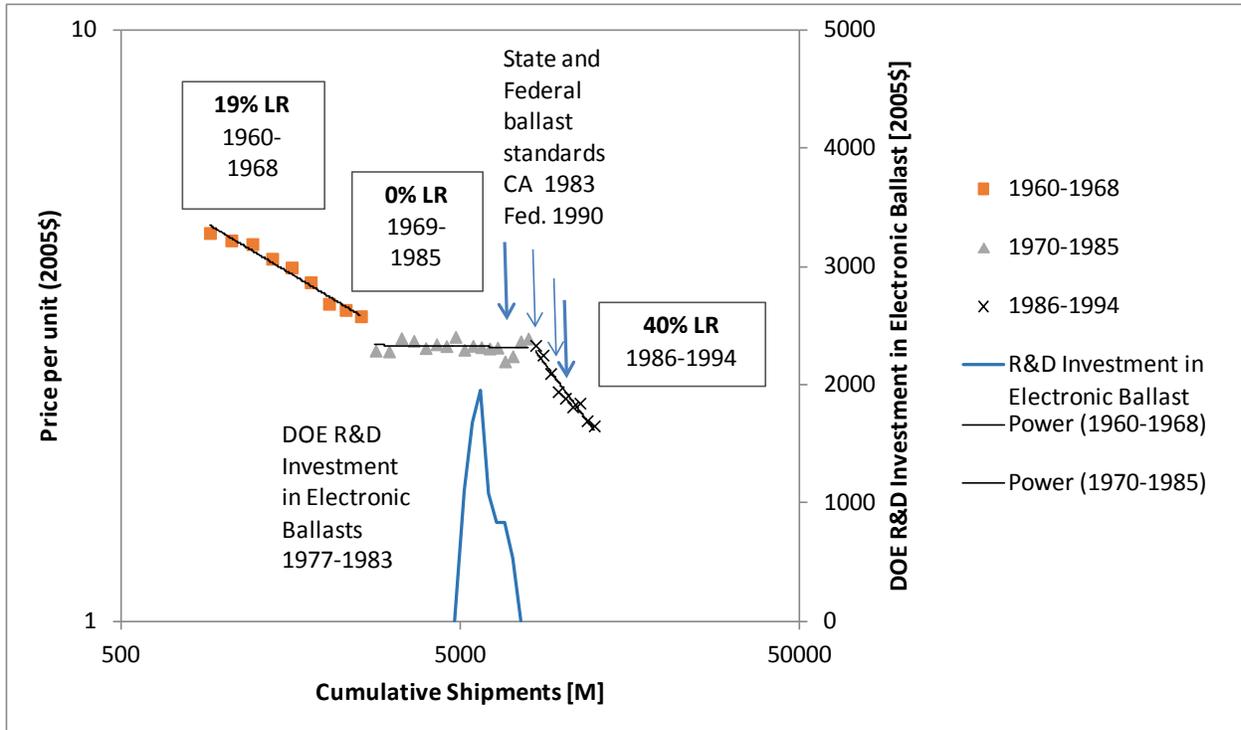
(c) General Service Fluorescent Lighting
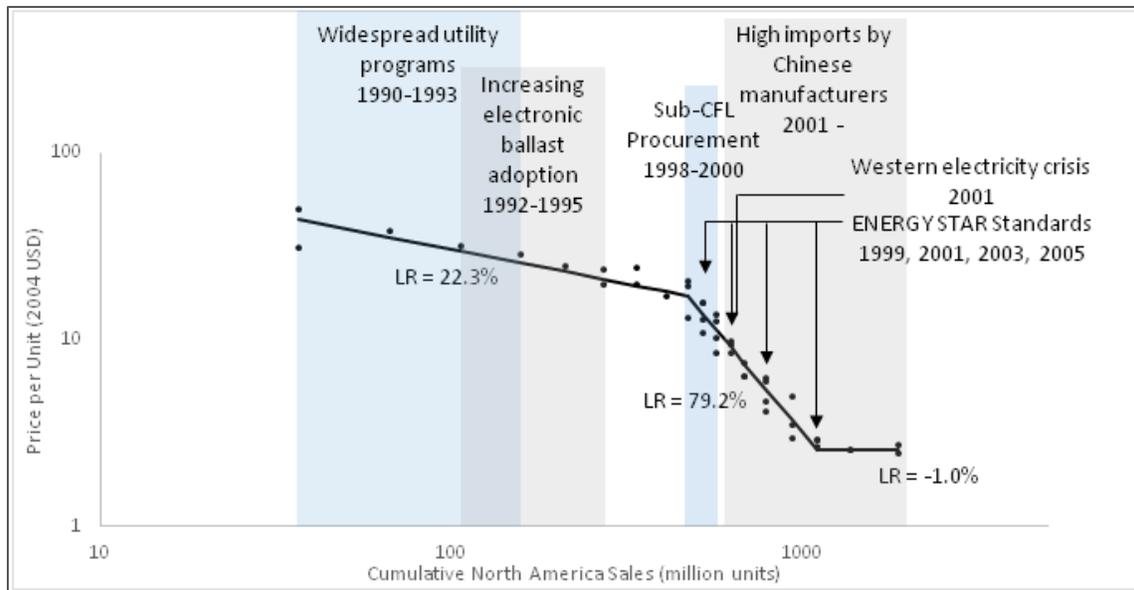
(d) Compact Fluorescent Lighting
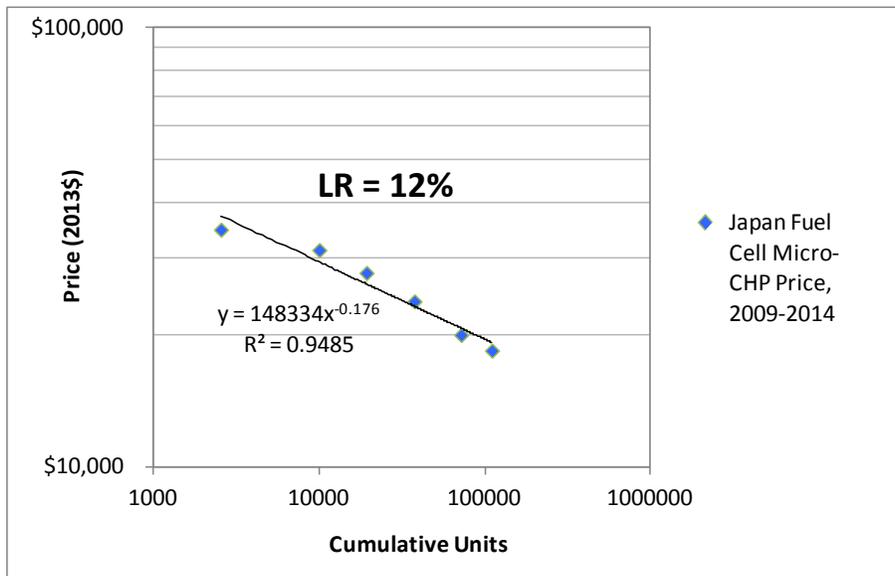
(d) Japanese Micro-CHP Fuel Cell Systems
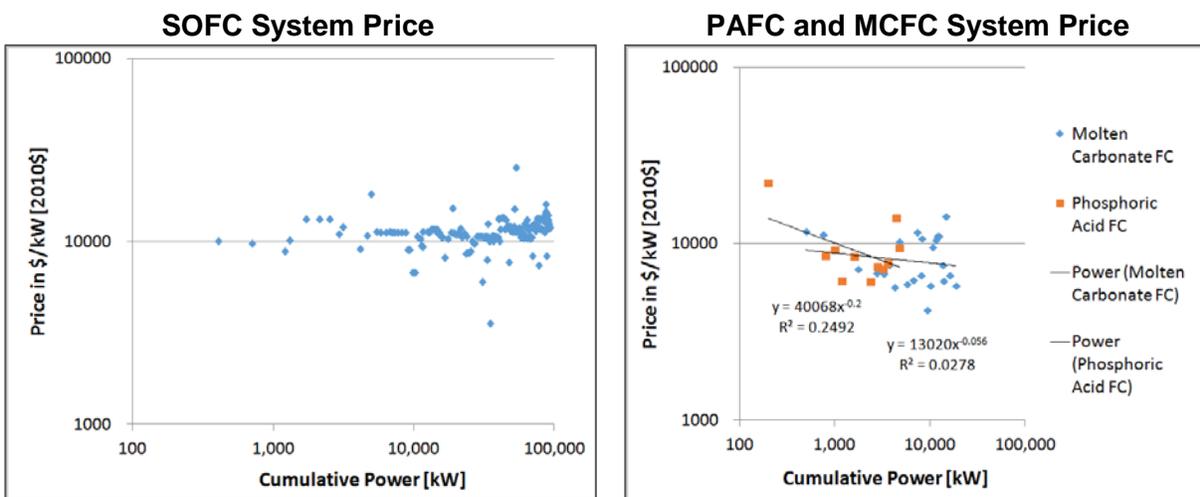
(f) Stationary fuel cell systems in Califronia.
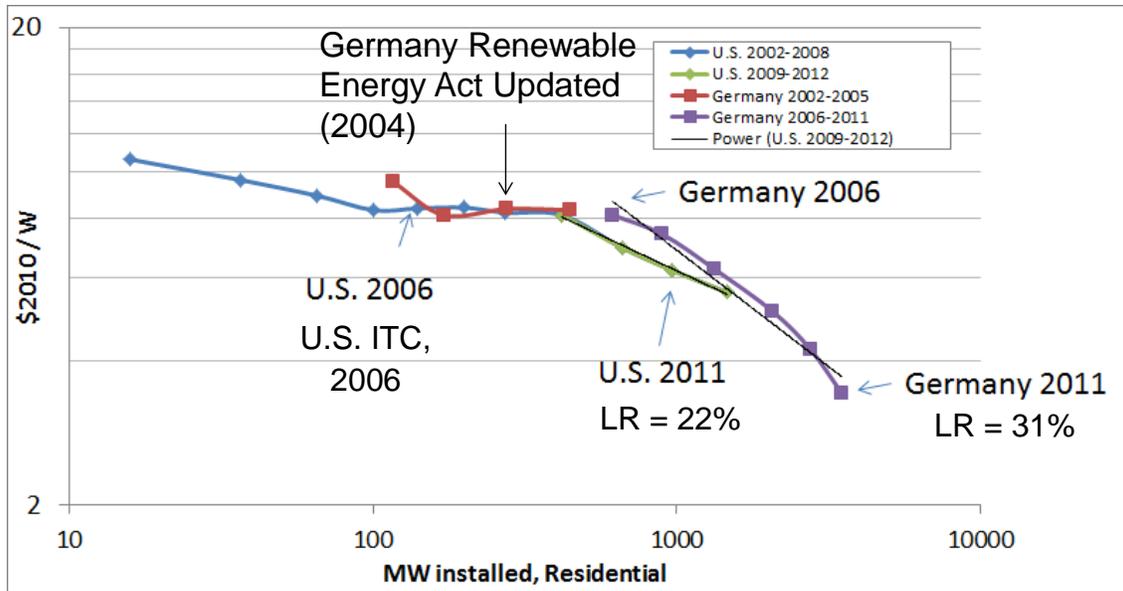
(e) Installed costs of residential solar PV

(f) LED lighting (A-lamps)
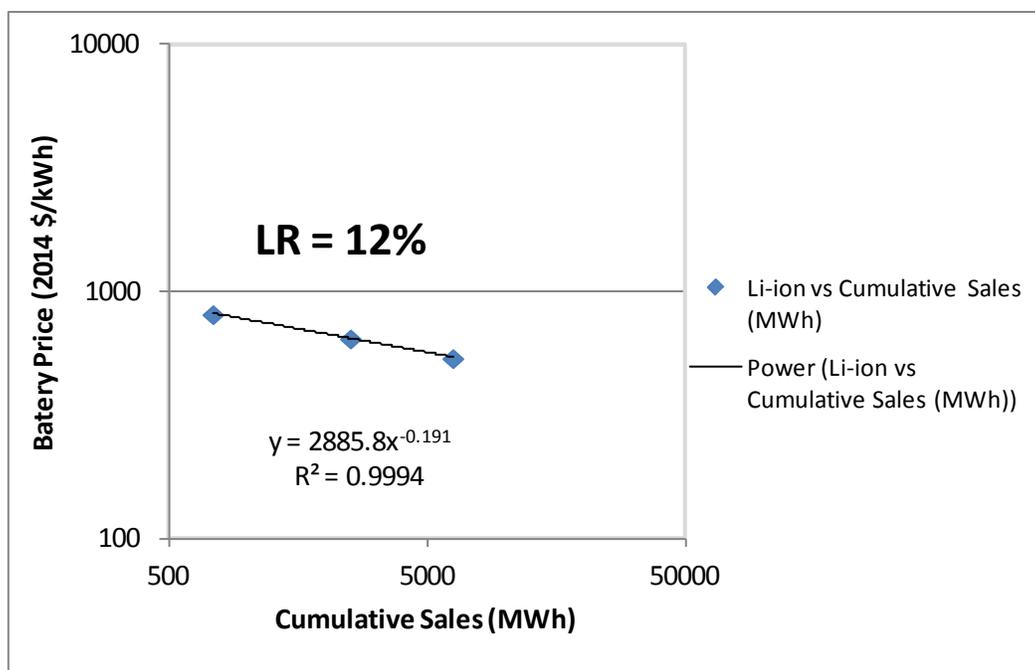
(g) Li-ion Batteries

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

3. 1. Electronic and Magnetic Ballasts

Ballasts provide voltage and current control for fluorescent lighting bulbs (or lamps), including 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 have had multiple deployment phases since their initial development in the 1970s. They were 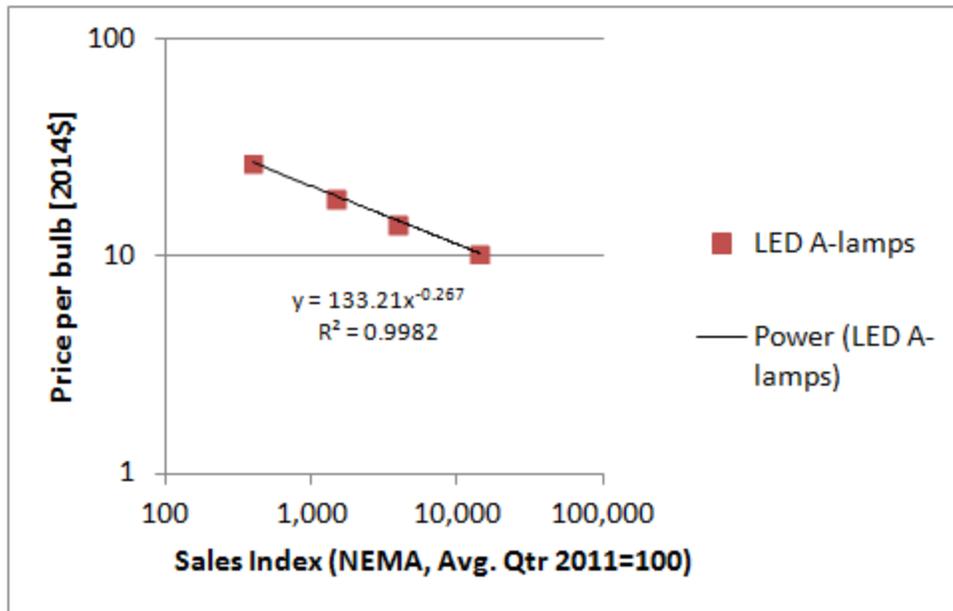examined at some length in the National Academy of Sciences (NAS) "Was it Worth It?" study on the costs and benefits of public energy efficiency investments (NAS, 2001). The study highlights the cost effectiveness of initial R&D investment of the DOE in the seven year period from 1977 – 1983. This was a multi-year effort led by LBNL to evaluate electronic ballast technology and develop 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. High cost of 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 for electronic ballasts 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 beyond the first seven years of R&D investment and is not focused on the impact of deployment programs or tracking innovation metrics of the technology.

This initial technology demonstration in the early 1980s is thought to have led to large companies making R&D and capital investments by the mid to late 1980s. Innovation in performance, cost reduction, and product envelope ensued, and electronic ballasts began to penetrate the market in 1988. Electronic ballasts increased in market share rapidly starting in the early 1990s to about to 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 the late 1980s (New York, Massachusetts, Connecticut, and Florida). The first federal standards for lighting ballasts were introduced in 1990, and revised in 1993, 1995, 2000, and 2011.

Rebate programs and standards were key factors in encouraging 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® Program and Green Lights (now merged with ENERGY STAR), the Federal Energy Management Program's introduction of energy-efficient technology in federal facilities, 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 the 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.

3. 2. Electronic and Magnetic Ballast Experience Curves

Data 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, and found that the experience curve exhibits piecewise-linear behavior with an initial learning rate of 8% from 1986 to 1992 followed by a higher learning rate of 23% after. Note that an earlier reference by Weiss at al. (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 and Sanstad (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). Again, there is a shift in the observed learning rate from 15% prior to 1990 to 40% after 1990. Note also that the market price increased in 1990 due to a shift to efficient ballasts from 37% market share to almost 100% after the standard.

3.3. General Service Fluorescent Lighting (GSFL)

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]

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 19% learning rate from 1960 to 1968, virtually flat (0%) learning rate from 1969 to 1985, and then a 40% learning rate from 1985 to 1994. GSFLs are distinct from other technologies as they represent lamps or fluorescent tubes that are part of a system, as a fluorescent tube lighting unit comprises both a bulb and ballast. 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 described above.

Lamp "service level" as a function of time is also confirmed to not be decreasing on a per unit basis over time. If this were the case then decreasing cost could simply be due to lower service levels.

3.4. Compact Fluorescent Lighting (CFL)

A brief description is provided here with a more extensive analysis and discussion found in Smith et al. (2015). Price 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 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. North American data is shown in this report for CFLs since ballast and GSFL experience curve data is also for the U.S. market. Smith et al. (2015) also discusses the international experience curve and arrives at similar break points in the learning rate.

The 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 22.3% observed prior to 1998 and a rate of 79.2% after 1998. There is also a substantial learning rate change after 2005, where the curve essentially flattens out. This may be 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 et al. (2006). Significant downturn during steady implementation of standards and programs has been seen in appliances, as previously discussed (Van Buskirk et al., 2015).

Many deployment programs as well as exogenous events correlate to the sustained downturn seen in the experience curves. 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 et al., 2008). An extensive discussion of deployment programs and linkages to the learning rate are provided in Smith et al. (2015).

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

3.5. Stationary Fuel Cell Systems

Data sources for micro-CHP in Japan are from trade show and technical conference presentations and publically available market reports. Data for California fuel cells 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 U.S. Department of Energy (U.S. DOE) has historically invested in fuel cell technology development and deployment of FC systems (e.g. 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 systems[4]. Thus, post incentive cost can be about half of the pre-incentive price. Note also that over time, greater performance monitoring and reporting requirements for the SGIP program may have contributed to greater system prices. The market in California is typically for commercial power and CHP systems with system powers from 200kW to 500kW.

The Japan micro-CHP program (also known as "Ene-farm") supports small residential power and CHP units (0.7-1kW). The program became commercialized in 2009 with generous rebates per unit decreasing over time ($12,000 per unit in 2009 to $3330 in 2014). The Japanese government has set a goal of achieving $5000/unit price in 2030, and market adoption targets of 1.4M units in 2020 and 5.3M 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).

Japan micro CHP had a learning rate of 12% from 2009 to 2014 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.

3.6. Installed costs of residential solar PV

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 cost of PV are taken from recent "Tracking the Sun" reports by LBNL, a Germany/U.S. installed cost study also from LBNL (Seel, 2014), and various market reports on the size of the German and U.S. residential solar PV market.

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[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.

Plotting this data, we observe a 31% learning rate in recent years in Germany for the cost of installed residential PV and a learning rate of 22% 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. Seel et al. highlights three key areas for Germany to U.S. cost differences: (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 are assumed to have made customer acquisition costs much lower in Germany.

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 percent tax credit for solar systems on residential and commercial properties[6] 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 providing $2.1 billion to businesses, nonprofit organizations, public agencies and homeowners who adopt solar technologies[7].

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 costs for systems less than 10kW from 59% fifteen years ago[8]) and thus, costs such as inverter costs, installation and other soft costs are more important than module costs in driving the overall installed cost of solar PV.

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

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

[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.
[7] https://energycenter.org/programs/california-solar-initiative, accessed 2 April 2015.
[8] http://emp.lbl.gov/sites/all/files/lbnl-6350e.pdf Tracking the Sun VI, page 17.

3.7. LED lighting

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 replacements. Market sales are taken from the National Electrical Manufacturers Association (NEMA) quarterly reports for sales and utilize EIA data for prices[9]. There is limited data for A19 product since these LED-based lamps were only introduced a few years ago. We compute a learning rate of 17%, 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.

The U.S. Department of Energy 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.[10]

3.8.Li-ion batteries

Price data for lithium-ion automotive batteries utilized data from Canis (2010), Bloomberg, and Navigant.[11] 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 PHEV and 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 Internet[12] to compute the total MWh in the global market.

An early 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 NiMH (LR= 9-10%) from Kalhammer (2007), but note that this reference also has very scant data on NiMH prices.

The U.S. DOE and the state of California have a long history of research, development and deployment of electric vehicles. From 1976- 1981 the DOE initiated and conducted R&D in hybrid electric vehicles and electric vehicles (HEV/EV). 1990 saw the implementation of the first Zero Emissions Vehicle (ZEV) Mandate in California. In 1992 the USCAR was established, an industry research consortium for

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[9] 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.

[10] http://programs.dsireusa.org/system/program, accessed 1 April 2015.

[11] 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.

[12] See for example, http://evobsession.com/world-electrified-vehicle-sales-2013/, accessed on 26 October, 2014.

advanced vehicles including USABC (an advanced battery consortium). From 1993-2005, Partnership for a New Generation of Vehicles (PNGV) was formed, a public/private partnership with the goals of achieving an 80mpg passenger vehicle and developing advanced manufacturing technologies and focusing on NiMH and Li-ion batteries. 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 ARRA (American Recovery and Re-investment Act) 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 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 rebates[13].

3.9. Other Studies

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.

3. 10. Heat Pumps in Switzerland

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.

3.11. U.S. Appliances

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 polices. 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, shown in Table 3, 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." 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).

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[13] http://driveclean.ca.gov/pev/Costs/Vehicles.php, accessed 1 April 2015.

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)

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%

4. 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 installed costs of 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).

In many cases we are updating experience curves for technologies that have been reported in the past with more recent data. For example, electronic ballasts had an earlier reported learning rate of 10% (Weiss et al., 2009) but we find a much higher learning rate starting in the early 1990s. This work underscores the need for regular periodic updates to ascertain the latest experience curves and any changes in the learning rate.

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. 2015 for more details).

In the case of U.S. appliance experience curves from Buskirk et al. (2015) the introduction and updating of appliance standards consistently show an accelerated long term decline in appliance life-cycle costs (which include operating costs).

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 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 and price per kWh for Li-ion automotive batteries.

4.1. The Importance of Exploration and Increasing Degrees of Freedom

A general qualitative comment on learning rates is that one can think of the learning rate as being dependent on exploration and "trying new things." The more novel approaches are tried, the higher likelihood for faster learning.[14] An illuminating example of this is from the semiconductor lithography industry. Lithography is a technology enabler for the industry to print finer and finer (narrower) lines and spaces to form integrated circuit designs onto semiconductor or metal substrates, and is thus a key enabler for Moore's Law exponentially shrinking feature sizes. For many years, the industry referred to the "1 micron-barrier" as the limit for known optical lithography due to diffraction-limited resolution. An experience curve of minimum feature size versus cumulative volume in this case may be expected to flatten out as the perceived limit of resolution is reached. An optical lithographic system consists of the following key subsystems: (1) source of illumination e.g. mercury arc source or a laser source; (2) illumination system (e.g. apertures and lens); (3) imaging system consisting of the master stencil pattern or "mask" that is being imaged and the optical imaging system itself (again a complex system of lens that typically de-magnifies the mask pattern with some reduction factor onto a silicon wafer); (4) the imaging film, or "photo-resist" on the wafer substrate that records the imaged pattern and is then developed by a wet process similar to that used to develop photographic film.   The key point is that systematic innovation in all four key areas were achieved with intensive industry activity to break through the 1-micron barrier: the development of new, lower wavelength radiation sources; optical engineering and optimization of illumination system and apertures; ever more complex optical systems and improvement in lens design, performance and tolerances; advanced "phase-shift" mask design and technology; and finally development of higher resolution, higher performance photo-resists capable of delineating ever-finer features (Pease and Chou, 2008).

Intensive efforts were made in all of these areas to remain competitive within the industry and the industry continually pushed down the minimum feature size to well below 0.25um today. Maximum learning and resolution improvement in this case was achieved by looking comprehensively at each subsystem and wringing the maximum performance gain from each subsystem. If there were not the same level of exploration, the industry would not have achieved the same level of lithographic performance improvement.   Conversely if there were not the right set of drivers – market driven competitive forces in this case, the industry would not have explored all of these subsystems so

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[14] Robert van Buskirk, private communication, 28 January 2015

thoroughly and perhaps there would not have been the innovation environment that led to the development of novel phase-shifting masks for example.

Thus it is possible that the imposition of deployment programs such as efficiency standards or incentive programs increase the degree of exploration or "degrees of freedom" in a perhaps under-studied area, and thus contributes to a learning rate that would have otherwise have been flatter or more static. This may work in the case of efficiency standards where a supplier firm may see the need to meet the upcoming standard more cost effectively while for incentive programs, supplier firms may anticipate a sustained, growing market and decide to invest in more developing advanced technologies with the prospect of higher performance or lower cost. This particular modeling framework deserves further study, especially for the case of GSFL in the 1970s when the learning rate was essentially zero for over a decade.

4.2. Directions for Further Work

Key unanswered questions include the delineation of prices versus underlying costs; learning rates for domestic versus international markets; further development of the interplay of deployment programs and technological innovation, and the interplay of component cost reductions and system costs or prices. 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 phase).

For deployment programs, how best should analysts 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[15] but the price-to-cost time lag effect should be an area for further study and better quantification.

5. Conclusions

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.

We have presented empirical experience curves for eight technologies (electronic ballasts, magnetic ballasts, GSFL, CFLs, fuel cell systems, installed cost of solar PV, LED lighting, and Li-ion batteries). Five of the eight have curves have observed bends downward in the shape of the experience curve (electronic ballasts, magnetic ballasts, GSFL, CFLs, installed cost 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.

Clearly 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, together with the earlier work by Buskirk et al. (2014) suggest 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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[15] 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).

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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 an 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 product[16]" 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 year[17]; (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.

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[16] For electronic ballasts, lumens per unit refer to the lumens level of the accompanying fluorescent lamp that the ballast supports.
[17] 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.

A.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 A-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.

Table A-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				
Less than 40W		*31*	*90%*	*1498*
High Output		*141*	*10%*	*6900*
Assumed Luminous Efficacy	49			
Avg. lumens/ unit				**2039**
2004 Product Types				
All 32W		*32*	*79%*	*1897*
All 59W		*59*	*2%*	*3499*
Not specified		*30*	*3%*	*1779*
High output		*116*	*6%*	*6900*
CFL 26W		*26*	*8%*	*1542*
CFL >26W		*30*	*2%*	*1779*
Assumed Luminous Efficacy	59			
Avg. lumens/ unit				**2199**

From Table A-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.

A.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 x 75% and P_2 x 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) x 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 A-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 A-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				
Recurring				
Slimline		*68*	*17%*	*2400*
Circular		*57*	*3%*	*2000*
High Output > 80mA		*196*	*7%*	*6900*
Other, < 40W		*31*	*15%*	*1100*
Other, > 40W		*77*	*58%*	*2725*
Assumed Luminous Efficacy	35			
Avg. lumens/ unit				**2703**
1992 Product Types				
Recurring				
Slimline		*49*	*11%*	*2400*
Circular		*41*	*1%*	*2000*
High Output > 80mA		*141*	*6%*	*6900*
Other, < 30W		*23*	*13%*	*1100*
Other, > 30W		*56*	*69%*	*2725*
Assumed Luminous Efficacy	49			
Avg. lumens/ unit				**2700**