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A retrospective analysis of compact fluorescent lamp experience curves and their correlations to deployment programs

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HIGHLIGHTS

- We develop a segmented regression technique to estimate historical CFL learning curves.
- CFL experience curves do not have a constant learning rate.
- CFLs exhibited a learning rate of approximately 21% from 1990 to 1997.
- The CFL learning rate significantly increased after 1998.
- Increased CFL learning rate is correlated to technology deployment programs.

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ABSTRACT

Experience curves are useful for understanding technology development and can aid in the design and analysis of market transformation programs. Here, we employ a novel approach to create experience curves, to examine both global and North American compact fluorescent lamp (CFL) data for the years 1990–2007. We move away from the prevailing method of fitting a single, constant, exponential curve to data and instead search for break points where changes in the learning rate may have occurred. Our analysis suggests a learning rate of approximately 21% for the period of 1990–1997, and 51% and 79% in global and North American datasets, respectively, after 1998. We use price data for this analysis; therefore our learning rates encompass developments beyond typical "learning by doing", including supply chain impacts such as market competition. We examine correlations between North American learning rates and the initiation of new programs, abrupt technological advances, and economic and political events, and find an increased learning rate associated with design advancements and federal standards programs. Our findings support the use of segmented experience curves for retrospective and prospective technology analysis, and may imply that investments in technology programs have contributed to an increase of the CFL learning rate.

1. Introduction

1.1. Compact fluorescent lamps background

Compact fluorescent lamps (CFLs), first invented in the 1970s, are valued for their energy efficiency and compatibility with existing fixture designs. Early adoption of CFLs was hindered by high product prices, low electricity prices, consumer resistance to change, and poor product performance in areas such as color quality, flickering, and start-up time (PNNL, 2006). But even as product performance improved and life-cycle costs were reduced throughout the 1990s, consumer awareness and high initial cost limited wider scale adoption.

In this work, we examine empirical market data and program activities in an experience curve framework in order to review historical development and determine to what extent deployment and other activities affected the CFL market. An underlying motivation for reviewing the market development of CFLs is to improve our understanding of the role of technological advancements, economic incentives, and external events (such as trade sanctions and electricity prices) for a unique technology that experienced several technical changes and underwent several market changes. Section 4 discusses some of the changes and influences on the CFL market that make it a technology of interest.

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1.2. Technology learning

Learning curves and experience curves are a common framework for assessing how a technology's cost reduces with increasing production volume (Taylor and Fujita, 2013). Learning curves specifically examine the relationship between cumulative production and labor costs and are parameterized by a "learning rate" which describes the improvement in worker efficiency that comes with experience. More broadly, experience curves relate cumulative production with total unit cost or market price and are also parametrized by a learning rate as described below Empirically observed price reduction may be due to a wide range of factors such as economies of scale, improved manufacturing process control, technological improvements such as enhanced design or greater parts-integration, increased competition, material or component cost reductions, etc. Therefore, the learning rate parameter on a price-based experience curve encompasses many improvements throughout the supply chain beyond worker efficiency. These curves are empirically found to follow a power law, as shown in Eq. (1), with the rate of cost reduction a power law function of cumulative production volume.

$$C(t_2)/C(t_1) = \left(V(t_2)/V(t_1)\right)^{-b} \tag{1}$$

where:

$C(t_2)$=cost or price at time t_2
$V(t_2)$=cumulative production volume at time t_2.
$C(t_1)$=cost or price at time t_1.
$V(t_1)$=cumulative production volume at time t_1.
b=empirically observed parameter.

The percent by which cost decreases for every doubling of production volume is referred to as the learning rate ($LR=1–2^{-b}$).

1.3. Prior CFL learning and experience curve literature

Existing CFL learning rate literature contains many issues with transparency, methodology, and comparability. Iwafune (2000) estimated CFL learning rates from 1992 to 1998 to be approximately 22% for price per thousand lumens of delivered lighting output. Disaggregating into specific product types, the study reported learning rates of 41–16%. These curves were constructed using four years of data with a three-year gap before the final year ('92, '93, '94, '98), a small number of years relative to the history of CFLs in the marketplace. The missing years force data interpolation, particularly when assuming a constant learning rate. For example, excluding the last year of data as shown in Fig. 1 of this report gives a learning rate of 37% as opposed to the reported value of 21%, with a much higher correlation coefficient. In addition, the mixed units on the learning curve plot (price per thousand lumens versus price per cumulative unit production), are not consistent with other works' methods of using consistent units on both axes. Ellis (2007) created an experience curve with an often-cited learning rate of 10%, using data obtained from the Australian Greenhouse Office (AGO, 2006) and an unreferenced source cited as "Du Pont, 2005". Unfortunately we found the creation and reporting of this learning rate unsatisfactory, due to issues such as data misinterpretation (annual sales used as cumulative sales) and possible calculation errors (a recreated curve using their data yields a drastically different rate than what is reported). Weiss et al. (2008) developed a global CFL experience curve for 1988–2006 and found a learning rate of 16–21% for price per watt-equivalent, while Gerke et al. (2014) found a learning rate of 14% for 1992–1994, using US-only production and *cost* data.

From this study of historically reported data, we therefore see the need for new development of the CFL experience curve. In addition, we desire a curve that is not constrained to a constant learning rate, as informed by past works relating changes in product learning rates to public programs (Grübler et al., 1998; Van Buskirk et al., 2014; Wei et al., in press). In this work, we hope to reconcile the many differences in the reported CFL learning rates and present defensible and more easily interpretable learning rates.

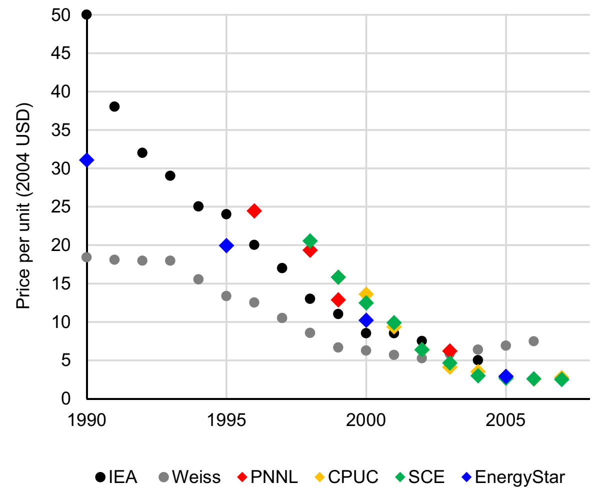

Fig. 1. Aggregated price data from six sources. Two international sources: IEA (Waide, 2010), Weiss et al. (2008); four US sources: PNNL (2006), CPUC (The Cadmus Group, Inc., 2010), Southern California Edison (Itron, Inc., 2008), and ENERGY STAR (Bickel at al., 2010).

2. Challenges with experience curve development

2.1. Data discrepancies

Experience curves require two datasets for a given timeframe: cost or price and cumulative production. Often, information must be collected from multiple sources and processed, distilled, and combined into useful sets. Details such as product types, purchasing scale, distribution channel, and geographical region, are often unreported with the data and can vary widely for a given technology. Cost data is further challenged by price versus cost confusion, prices normalized to varying performance metrics (e.g., \$/thousand lumens) and whether the currency-year units are reported (e.g., 2010 US dollars). Often-available *annual* production data cannot be converted to the needed *cumulative* production without an initial point, i.e., the cumulative production prior to the first year of data. There is therefore enormous difficulty in determining a definitive or canonical experience curve for a technology, since many learning rates may be derived depending on one's interpretation of the data.

All of these difficulties are in force when deriving an experience curve for CFLs, as many gaps and inconsistencies are present in existing data. Moreover, several reported learning rates do not explicitly reference the source of data, units, or details about specific product and sales conditions. We manage these challenges by collecting readily available price and production data that is not meant to be representative of any specific product or bulb type, but the market as a whole. By analyzing the market on a per-unit basis, where a "unit" represents a single bulb (often referred to as a "lamp"), we are able to capitalize on a larger database of price and production data. Other metrics such as lumens or wattage of the units are not readily available to normalize the units of data. This distinction is important when comparing results to other studies of CFLs or other lighting products that may be normalized by service level (lumen) or energy use (watt). Details about the datasets used any known characteristics of the products represented are discussed in Sections 3.1 and 3.2.

2.2. System boundary selection

Boundaries of the technology development system are a key factor in what data is collected, how the data are interpreted, and how to conduct the experience curve analysis. Local prices and adoption patterns often vary and therefore neither can be assumed to be consistent across regions. In this work we develop an experience curve for both the global and North American CFL markets. This boundary decision is motivated by the vastly different adoption curves for the two areas and the many social, economic, and political programs which contributed to development of CFLs and their market adoption. We present both curves for comparison and discussion.

2.3. Time dependence

The original empirical observations that led to the study of learning curves showed a single power law relationship between a cost and production variable (Wright, 1936), implying that the learning rate stays constant over time. This assumption remains the prevailing approach for deriving learning curves. Grübler et al. (1998) proposes that for long time-scales of analysis that span multiple technological "stages" of a product, a different learning rate exists in each stage. They suggest that in general, learning rates decrease as a technology moves through phases of innovation, niche-market commercialization, and diffusion, and then become effectively zero during market saturation. Alternatively, recent work by Van Buskirk et al. (2014) allows for the possibility of a time-varying learning rate over an undefined time scale. They compute learning rates for various appliances that increase, markedly, after adoption of product standards. In either case, a non-constant learning rate allows for the ability to observe distinct changes in a technology's development, pointing to time-varying factors that affect the learning rate such as research breakthroughs, government policies, and market expansion.

3. Methods for experience curve creation

3.1. Price data collection

Data collected for this analysis is meant to be representative of average CFLs, inclusive of all brands, product types, and power levels. We collected price data from a variety of academic journal articles and industry reports, and converted the data to 2004 US dollars (USD) units using Bureau of Labor Statistics Consumer Price Index and currency conversion records reported by the U.S. Federal Reserve System. Data from six sources are shown in Fig. 1, and are described as follows:

- A 2006 IEA report reviewing global appliance standards and codes presents global price and sales data for screw-based CFL bulbs from 1990 to 2004 in the form of a learning curve (Ellis, 2007).
- We derive national average CFL prices for 1998–2007 from regional price data reported in a 2008 study for Southern California Edison (SCE) (Itron, 2008). This data represents typical medium-size screw-based CFLs, the majority of which are spiral (or "twister") shape.
- A report for the California Public Utilities Commission (CPUC) reported 1999–2007 average retail prices for the U.S., primarily using data from a SCE report (The Cadmus Group, Inc., 2010).
- In 2006, a Pacific Northwest National Laboratory (PNNL) report discussed broadly the CFL market, mentioning the price of CFLs over occasional years from 1996 to 2003 (PNNL, 2006). This report, and the prices noted, was not specific to any region or CFL type.
- ENERGY STAR's CFL Market Profile references price points in their discussion on CFLs, without pointing to specific products that those prices represented (Bickel et al., 2010).
- Price data from Weiss et al. (2008) represents CFL bulbs that are equivalent to a 75-Watt incandescent. Weiss's data is sourced from Dutch sales information, along with a 2007 report that lists CFL price data for intermittent years, for various countries across Europe (Oosterhuis, 2007).

The rate of change between the datasets and across regions generally appear to be similar, suggesting that price trends may not vary significantly between regional and global markets. For the US, data prior to 1995 is sparse, and therefore it is difficult to conclude the extent of differences between US and global data. Overall, we see that the price of CFL bulbs have declined significantly for two decades. The exception is the data from Weiss et al., which shows essentially no price decline from 1990 to 1994, and a price increase from 2002 to 2006. This price behavior is difficult to explain and is not seen in the other datasets, but could possibly be a result of the multiple currency and inflation-related adjustments that were applied to create the final dataset. Therefore, we include the Weiss et al. data in our analysis with caution.

3.2. Production data collection and processing

Production data was compiled from three main sources of sales estimates. Table 1 summarizes the collected data set's type, region, and timescale. Data from Iwafune includes an estimate for total sales prior to 1990, which allows cumulative totals to be computed for the North America case. To compute a learning rate, we combine the resulting data into two consistent datasets: global and North America.

Global cumulative production data was very consistent across our three datasets, so a simple averaging was done to create a single experience curve. The North America cumulative production data, however, required more extensive manipulation. To determine the consistency of data from Iwafune and IEA for different time periods, we examined the percentage of global sales credited to North America. These values, including data interpolation for 1998–1999, are shown in Fig. 2 and the resulting trend appears reasonable. The final cumulative sales curve was then constructed using data from Iwafune for 1990–1997, interpolated data for 1998–1999 (North American percentage times annual global sales), and IEA data for 2000–2007. Results for both global and North America production curves are shown in Fig. 3.

3.3. Segmented regression analysis

Various methods can be used to determine the change, or lack of change, in a power law regression parameter. For our analysis, we employ a segmented regression model, also referred to as multiple-phase regression, piecewise regression, or broken-line

Table 1
Summary of CFL production data gathered from three sources.

Source	Type	Region	Years
Iwafune (2000)	Cumulative production	Global	1990–1998
Iwafune (2000)	Annual sales	North America	1990–1997
AGO (2006)	Annual sales	Global	1990–2004
IEA (Waide, 2010)	Annual production	Global	1990–2007
IEA (Waide, 2010)	Annual production	North America	2000–2007

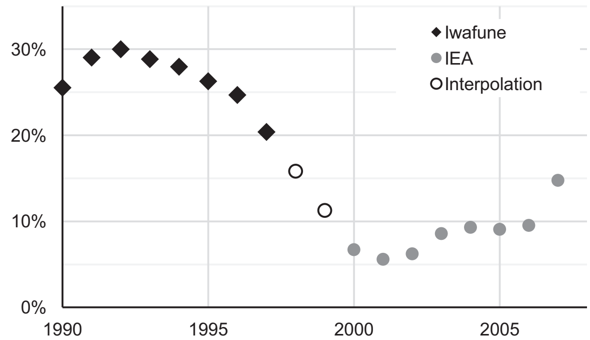

Fig. 2. Percent of global annual CFL production attributed to North America.

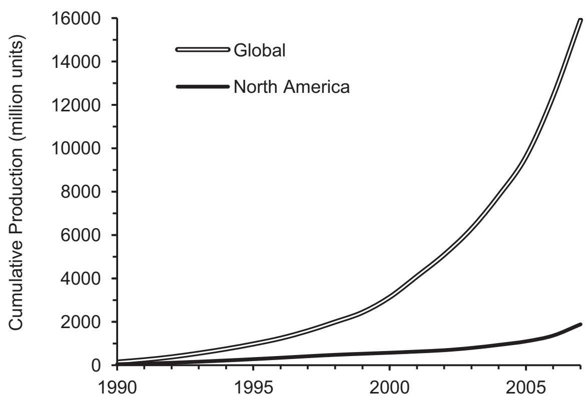

Fig. 3. Global and North America cumulative CFL production curves.

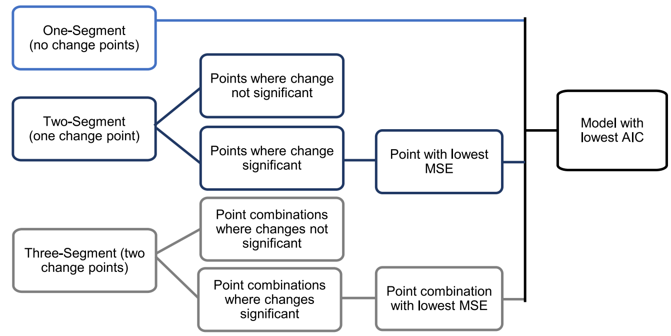

Fig. 4. Flowchart for computing one- and multiple- change point models.

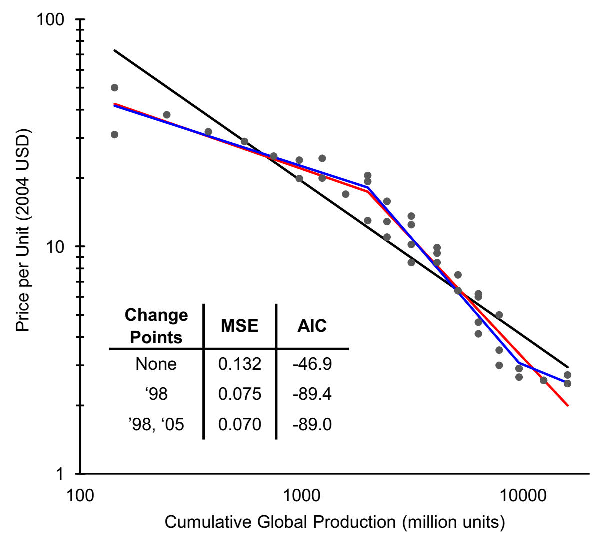

Fig. 5. Global CFL experience curves generated from segmented regression analysis.

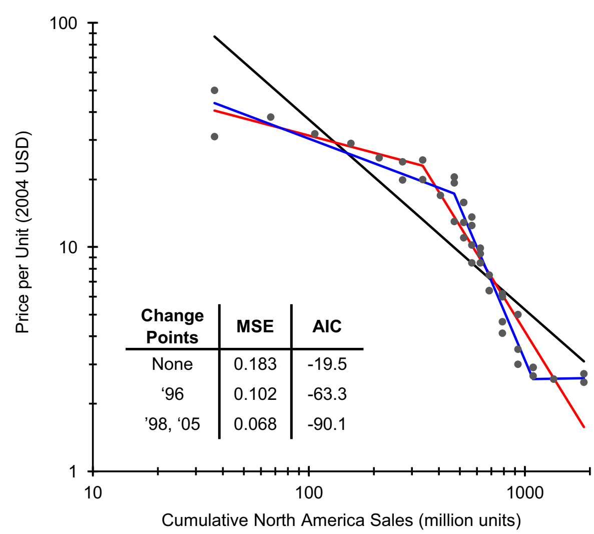

Fig. 6. North America CFL experience curves generated from segmented regression analysis.

regression. Such an analysis is straightforward to compute and interpret. Examples of its use are presented by Toms and Lesperance (2003) in the context of ecological thresholds and by Walter et al. (2014) in energy analysis.

The general regression equation used is as follows:

$$Y = \beta_0 + \beta_1(X) + \beta_2(X–C)^+ \tag{2}$$

where:

β_0 = constant.
β_1 = slope prior to change point.
β_2 = slope change at change point.
C = change point.
$(X-C)^+ = \{0 \text{ for } X \le C, \text{ X-C for } X > C\}$.

For a given change point, C, the term $(X\text{-}C)^+$ is derived, and the regression problem is solved using ordinary least squares fit. A significance test on the variable β_2 dictates the validity of a change in slope. To determine the most suitable change point(s), the regression problem is solved iteratively for a range of points in one-change and two-change scenarios. For two change points, an additional beta term is added to Eq. (2). The model with the lowest mean squared error (MSE) is chosen for each one-change, two-change, or no-change categories, then those models are compared based upon the Akaike Information Criterion (AIC) (Akaike, 1974). The MSE is not sufficient to compare across the three model types, as error will clearly be reduced as more change points are added. Therefore, the AIC is used to determine if the improvement in the model that occurs from adding a constraint (in this case, a second change point) justifies the loss of that degree of freedom. Fig. 4 shows the overall procedure for fitting a model to the experience curve data.

3.4. Results

Figs. 5 and 6 show the results for both the global and North America experience curves, respectively, along with the information used to select the best model. AIC is a relative metric, meaning that it is the difference between models that is indicative of which one is "better," while the number for one model alone does not say anything about its absolute goodness of fit. A more negative number for AIC indicates a better model, and therefore the models chosen are a one-change model for the global experience curve,

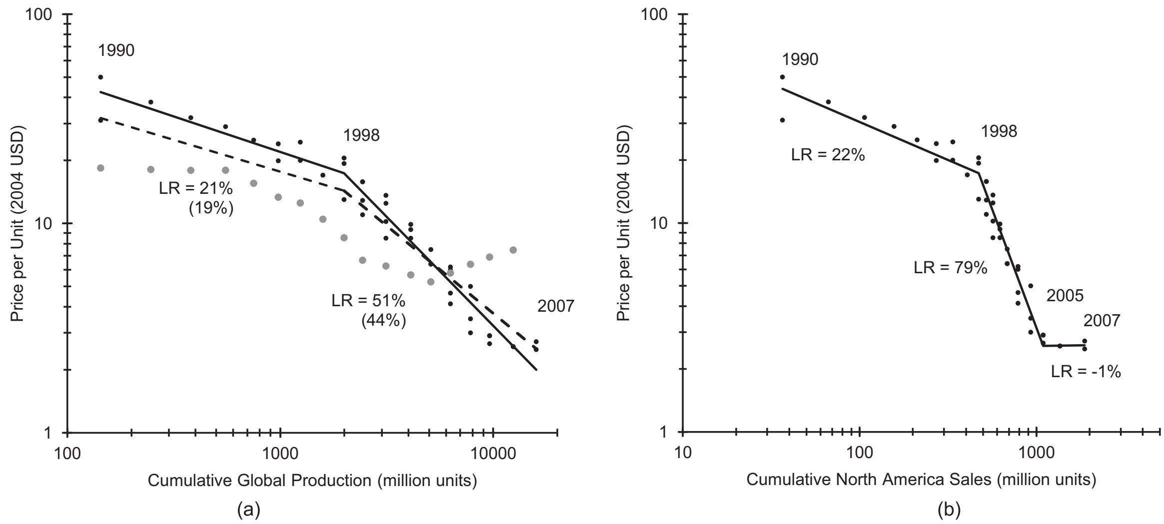

Fig. 7. (a) Global and (b) North America CFL experience curves. Global figure includes a second case, shown by the dashed line and parenthetical LRs, which includes Weiss et al. data (grey). Beginning, ending, and change point years are noted.

and a two-change model for the North America curve.

The final, best-fit experience curves, shown in Fig. 7, suggest interesting, while not surprising, behavior. The global experience curve shows a 21% learning rate from 1990 to 1998, followed by a 51% learning rate from 1998 to 2007. We also tested the curve including the Weiss et al. dataset, and while the learning rates differ (decreases of 2% and 7%, respectively), the key trend of a significant increase in 1998 persists. The North America market showed this trend as well, with a learning rate of 22% prior to, and 79% after, 1998. The North America market also appears to suggest a substantial learning rate change after 2005, where the curve essentially flattens out. One may note that the two-change global curve also showed this behavior, but the model was not more “suitable” than the one-change model, as in the case of North America. Calculated learning rates for 1990–1998 agree with reported learning rates in both Iwafune (2000) and Weiss et al. (2008), who reports a 21% learning rate for CFL units for the years 1988–2006. Weiss et al.'s resulting experience curve has a much better fit to the first half of the data compared to the more recent years, and we suspect that if a segmented regression had been used an increase in LR would have occurred during that time frame.

A significant shift to a faster learning rate similar to the downward bend seen in Fig. 7 has been seen in appliances during steady implementation of standards and programs, as previously discussed in Van Buskirk et al., 2014. Van Buskirk et al. (2014) found that the increase in learning rate was generally stronger for a learning curve with life-cycle cost as the y-axis, as opposed to purchase price. This implies that improvements in product efficiency, and therefore reductions in life-cycle cost, generally accompanied the price reductions seen after the implementation of standards. Efficiency data were not available for the products represented in the price data sets used in this report, and therefore life-cycle experience curves could not be constructed. Assuming that CFL efficiency has improved over time, a life-cycle cost experience curve may exhibit higher learning rates than those seen in this report.

The underlying theory of the experience curve is that sustained production creates a knowledge base that increases efficiency and reduces cost. By using consumer prices as opposed to true manufacturing costs, our experience curves include these efficiencies throughout the distribution and marketing processes. To what extent differences in the North America and global learning rates represent manufacturing learning as opposed to improved distribution and business management depends on the nature of the supply chain and market competition. Potential influences to these behaviors are discussed further in Section 4.

4. CFL learning rate influences

4.1. Public programs

Public deployment programs can influence a technology's cost through two primary mechanisms. Firstly, by increasing adoption, programs can move a technology “down” the experience curve in a shorter amount of time, potentially by inducing price savings through learning, economies of scale, and increased competition. Secondly, programs that increase a technology's market adoption can induce greater private research and development, either directly (through design competitions and product standards), or indirectly (through reinvestment of increased profits). This increased investment can lead to design breakthroughs that improve product performance and reduce costs. Some efforts have been made to link deployment programs with changes in price decline (Spurlock, 2013) and learning rate (Van Buskirk et al., 2014) of energy efficient technologies. Here we outline some of the most influential US programs and in Section 5 we discuss how these impacts are likely to have resulted in the learning rates seen in this work.

Early on in CFL development, utilities began incorporating the technology into energy efficiency programs. Beginning in the late 1980s, and continuing throughout the 1990s, these programs allowed utilities to generate revenue and meet policy goals. Utilities aimed to boost the CFL market through giveaways to consumers, retail rebate and coupon programs, manufacturer rebates, in-store and mail promotions, and education of both consumers and retailers (PNNL, 2006). These programs were largely scaled back in the mid-1990s as part of large utility budget cuts.

In 1998, the primary market barriers in integral CFL adoption were identified as price and size, which led the U.S. Department of Energy and Pacific Northwest National Laboratory to create a design and procurement program for new “sub-CFLs” (Ledbetter et al., 1999). Through this program, DOE aggregated buying power to increase demand and sold successful designs through a dedicated online retail channel. Successful designs met a variety of performance and energy criteria and, most importantly, size requirements that enabled them to fit in standard incandescent fixtures. Sales greatly exceeded expectations and 16 new models entered the market from the three participating manufacturers. In addition, similar products were introduced by non-participating manufacturers and sold through multiple retail channels.

ENERGY STAR's 1999 CFL specification set the first national standards for CFL energy efficiency, light quality, product performance, and testing procedures. The program qualified almost 200 models and 10 different manufacturers in its first year, growing to 1600 models and 100 manufacturers by 2010 (Bickel et al., 2010). These standards brought higher-quality products on the market increasing consumer satisfaction and therefore adoption (EPA, 2012). Shortly following the creation of ENERGY STAR requirements, the 2001 nationally coordinated lighting promotion “Change a Light, Change the World” educated consumers and promoted CFL technology, which further increased consumer awareness.

4.2. Component development

Previous work on experience curves has aimed to examine the relationship between a technology's cost reduction and that of its underlying components. Nemet (2006) modeled factors influencing the cost of photovoltaics and found module efficiency and cost of silicon to be significant explanatory variables. Ferioli et al. (2009) examined to what extent the learning of a technology could result entirely from learning in one or two components and found that products can often be described in the experience curve context as the sum of a component that experiences learning and has cost reductions and a component that does not. This argument is supported with a study of gas turbines, which shows that representing a product as the sum of two components with different learning rates (one of which may be zero), yields a better fit then considering the technology as one indivisible entity.

This is a particularly interesting concept in the case of CFLs, whose cost is largely made up by the ballast, which has undergone significant cost reductions of its own. Electronic ballasts began to replace magnetic ones in 1984 and accounted for 90% of CFL manufacturing costs throughout the late 1980s (Weiss et al., 2008). These ballasts demonstrated learning rates of 8% from 1986 to 1991 and 23% from 1992 to 2005 (Wei et al., in press) and therefore likely contributed to decreasing CFL costs during this time.

4.3. External events

Many other factors likely influenced CFL's development pattern. Electricity prices are often a driver for adoption of energy-efficient technologies as increasing prices make them more financially viable to consumers and generally raise awareness of energy consumption. Similarly, discrete events such as the Western US electricity crisis of 2001 can spark product development by creating demand for efficient products, increasing market competition, and triggering deployment programs. Although these events do not necessarily have a direct causal effect on the learning rate, the relationship to overall development is important to consider for analyzing the effect of deployment programs and forecasting future adoption and development.

CFL market competition was also driven by a production shift to low-income regions such as China (Weiss et al., 2008). In the mid- to late-1990s, Chinese companies increasingly entered the European CFL market flooding the market with low-cost (and often low-quality) products. This ultimately led to the European Union imposing steep tariffs in 2001 on Asian manufacturers, who then largely shifted their marketing efforts to North America (PNNL, 2006). This resulted in an increased supply of low-cost products, driving further price competition, and reducing profit margins (Weiss et al., 2008).

5. Discussion

5.1. Program correlation

Many of the programs and events discussed in Section 4 correlate to the sustained downturn seen in the North America experience curve, as shown in Fig. 8. The increased slope occurs after substantial technology developments had occurred in the sub-CFL procurement program, and during the time that ENERGY STAR standards are active. These programs, along with the external events happening at that time, created an environment for accelerated development. The relationship between these programs and the experience curve is important for both historical analysis and future technology projections. In the historical context, understanding the impact programs had on the technology's adoption and cost reductions can improve benefit analyses and help to inform future program designs. For technology projections, understanding events that are likely to occur (or end) during the time frame of interest can help inform how the experience curve will behave.

Causal relationships between specific deployment efforts and changes in the learning rate were outside the scope of this research. However, we believe this research is a critical first step in

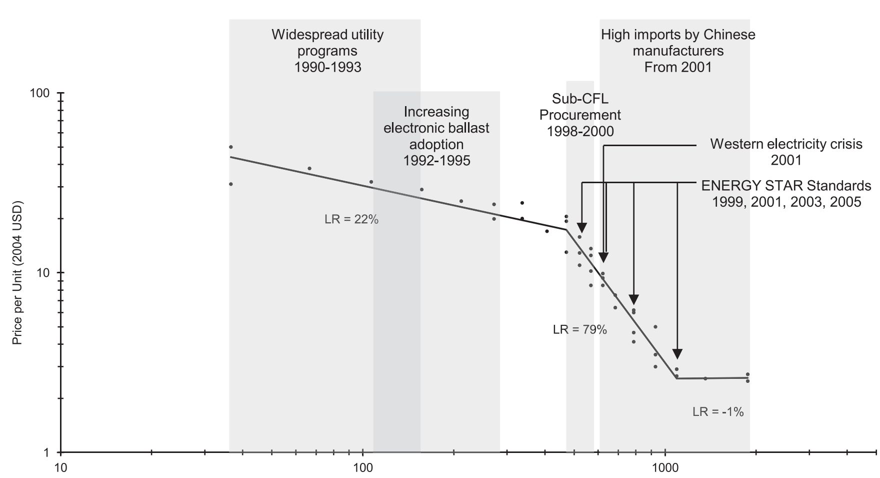

Fig. 8. North America CFL experience curve and influencing factors 1990–2007.

exploring causality in the years that indicate a change in the learning rates.

5.2. Global vs. North America Comparison

Although the global and North America experience curves generally show the same patterns, there are substantial differences, particularly after 1998 when North America shows a significantly higher learning rate (~80%) than the global rate (~50%). It is possible that significant differences exist between these two markets, and that the North American market's influences described in Chapter 4 caused an accelerated learning rate that was not realized globally. Another possibility is that CFLs exist in a truly global market, where prices change consistently over time in all regions, and the act of creating a learning curve with only a subset of global production (i.e. North America) gives the illusion of a much higher learning rate due to the lower production levels (i.e. the denominator of the learning rate). If it were the case, the North America-specific learning curve would not necessarily represent the full CFL market. However, our results would nonetheless draw attention to trends such as the flattening out of the curve from 2005 to 2007 which is present in the global market to a slightly lesser extent. This underlying trend could signal stagnation in learning and would have a significant effect on price predictions after 2007. Future work should further explore indicative market factors for selecting an experience curve boundary and assess the applicability of global versus regional experience curves.

5.3. Implications for historical analysis and forecasting

Historical CFL experience curves provide valuable insights for understanding the development of the technology. As shown above, CFLs experienced a steady sustained learning rate of ~20% through the 1990s and a sharply increased learning rate from 1998 to 2005. This information may be used to assess the impacts of various programs occurring during that time by considering the virtuous cycle of increasing adoption, subsequent cost reductions, and further adoption. The experience curve can also be used as a starting point to disaggregate cost reductions over time and identify key contributing factors. For example, price reductions throughout the 1990s may have been driven by economies of scale and manufacturing improvements, while later reductions in the 2000s may have resulted from decreased profit margin in the face of increasing competition. Methods to disaggregate these price reductions are further explored in another report (Wei et al., in press).

The experience curve methodology shown here also has potential to aid in technology forecasting efforts. If the two-segment curve is followed (as in the global case) one may expect further sustained reduction of costs, while the three-segment curve (as in the North America case) suggests a price floor has been reached. These different trajectories from 2005 to 2007 would result in vastly different results if projected forward. Further data collection beyond 2007 would be needed to determine if this flattening of the experience curve is a sustained change. Such behavior, where the learning rate reaches zero, is expected under assumptions seen in Grübler at al. (1998), which suggests that a product's learning rate reaches zero during market saturation and senescence stages. CFL market share peaked at ~23% in 2007, declining to ~18% by 2009, and has likely continued to decrease due to competition from LEDs (Bickel et al., 2010).

Beyond choosing which regression model to project into the future, the suite of possible future trajectories must also include additional changes in the learning rate. The changes in learning rate observed in this report, and others, indicate that reliance on historical learning rates to predict future development should be met with caution. While this may increase uncertainty in projections, it can more comprehensively capture the range of likely scenarios. Additional steps to understand causation between specific activities and changes in learning rate can help to reduce uncertainty within the realm of possible future trajectories.

6. Conclusions and policy implications

Segmented experience curves for CFLs both globally and in the North American market show learning rates of approximately 21% prior to 1998 with a substantially increased learning rate after 1998. The increased learning rate is likely due to a combination of factors: technology improvements, increased competition, and changing trade environment, along with public deployment programs. Data from 2005 to 2007 shows a reduction in learning rate which would have a substantial impact on future cost projections if sustained.

The CFL experience curve and methodology demonstrated in this work can be used to forecast future technology development and inform policy and program planning. Program planning often considers future technology adoption, and therefore cost reduction, when estimating program benefits. Use of all possible learning or experience curve scenarios is useful in policy planning to account for the many uncertainties surrounding technology development.

In addition, this work can inform future decision-making regarding new technologies for which a similar or adjacent technology's historical learning curve is available. For example, other lighting technologies such as LED will need substantial cost reductions before they are competitive with incumbent technologies. Knowledge about the learning rate demonstrated by CFLs and other lighting technologies, what contributed to those learning rates, and how they changed over time, is useful in projecting what range of learning rates LEDs may experience. This knowledge can also inform policy-makers what programs and policies appear to be correlated with an increased learning rate such as the DOE sub-CFL procurement program and ENERGY STAR national standards.

Future work should further examine the relationship between regional and sub-regional markets of a given technology, how component learning rates, particularly electronic ballasts, impacted overall product learning rate, and how CFL adoption over this time has saved energy and reduced greenhouse gases. In addition, application of the segmented regression method to other technologies with less mature markets can provide insights to how they are developing and how they may change in the future.

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