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Retrospective North American CFL Experience Curve Analysis and Correlation to Deployment Programs

Sarah Josephine Smith, Max Wei, Michael D. Sohn

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Abstract: Retrospective experience curves are a useful tool for understanding historic technology development, and can contribute to investment program analysis and future cost estimation efforts. This work documents our development of an analysis approach for deriving retrospective experience curves with a variable learning rate, and its application to develop an experience curve for compact fluorescent lamps for the global and North American markets over the years 1990-2007. Uncertainties and assumptions involved in interpreting data for our experience curve development are discussed, including the processing and transformation of empirical data, the selection of system boundaries, and the identification of historical changes in the learning rate over the course of 15 years. In the results that follow, we find that the learning rate has changed at least once from 1990-2007. We also explore if, and to what degree, public deployment programs may have contributed to an increased technology learning rate in North America. We observe correlations between the changes in the learning rate and the initiation of new policies, abrupt technological advances, including improvements to ballast technology, and economic and political events such as trade tariffs and electricity prices. Finally, we discuss how the findings of this work (1) support the use of segmented experience curves for retrospective and prospective analysis and (2) may imply that investments in technological research and development have contributed to a change in market adoption and penetration.

1 Introduction

1.1 Compact Fluorescent Lamps Background

Compact fluorescent lamps (CFLs), invented in the 1970s, are valued for their energy efficiency and ability to integrate with existing fixture designs. Early adoption of CFLs was hindered by high product prices and 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 1990's, consumer awareness and high initial cost limited wider scale adoption.

In this work, we aim to uncover various factors that led to the eventual success of the CFL market by examining empirical market data and program activities. An underlying motivation for reviewing the market penetration 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) from the perspective of a unique technology that experienced several technical changes and underwent several market changes. Section IV discusses some of the changes and influences on the CFL market that make it a technology of interest.

1.2 Technology Learning

In order to understand the development and acceptance of CFLs, it is beneficial to understand the drivers behind both the price and adoption patterns observed over time. Technology learning is widely accepted as a mechanism through which technology cost reductions can occur. The expression of this learning through experience and learning curves supports our understanding of

past development and forecasting future behaviors. Learning curves, which specifically examine the relationship between cumulative production and labor costs, are parameterized by a “learning rate” which describe the improvement in worker efficiency that comes with experience. More broadly, experience curves relate cumulative production with total cost or market price. 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 learning. As federal and state governments make investment and policy decisions in energy technology research, development, and deployment, the experience curve and resulting experience rate have the potential to provide indicators of advancement for purposes of program analyses.

Experience curves are a common framework for assessing technology learning and cost reduction with increasing production volume (Taylor, 2013). These curves are empirically found to follow a power law, with the rate of cost reduction a power law function of cumulative production volume:

$$\text{Equation 1: } C(t_2)/C(t_1) = (V(t_2)/V(t_1))^{-b}$$

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

and b is an empirically observed parameter. In essence, for every doubling in cumulative production volume:

$$\text{Equation 2: } C(t_2)/C(t_1) = 2^{-b}$$

The percent by which cost decreases for every doubling of production is referred to as the learning rate ($LR = 1 - 2^{-b}$), and the fraction of initial cost after every doubling of production is called the progress ratio ($PR = 1 - LR$). In the case of experience curves, prices may be used instead of costs throughout these equations.

1.3 Prior CFL Learning and Experience Curve Literature

We reviewed the existing CFL experience curve literature to first examine if any studies presented a suitable experience curve for our deployment correlation analysis. Due to past works relating changed learning rates to public programs (Van Buskirk et al., 2015, Wei et al., 2015), we desired a curve that was not constrained to a constant learning rate. No such curve previously existed in the literature. Further, no datasets existed that could be easily re-used to create a non-constant experience curve. Here we outline the issues in the existing literature that further demonstrate the difficulty and inexactness in creating CFL experience curves.

Weiss et al. (2008) developed a global CFL experience curve for 1988-2006 and compiled a comprehensive collection of previously developed experience curves for various building technologies. They found a learning rate of 16-21% for price per watt-equivalent. While it is common to observe learning rates on a per-service unit to account for performance improvements, the comparability across other learning rates which use different units is questionable. For example, Weiss explains that CFLs with different watt-equivalent values show significantly different learning rates, while on a per-lumen basis these differences go away.

Iwafune (2000) examined CFL price and characteristic trends throughout the 1980's and 1990's. They estimated learning rates from 1992 – 1998 to be approximately 21.6%. Their curve was created using data for most types of bulbs, with varying performance characteristics. Models that were excluded include some incomparable products such as integral CFLs with magnetic ballasts because very few were made, modular CFLs with magnetic ballast and reflector because they were exceedingly expensive, and modular CFLs with electronic ballasts and special low-temperature features because they were exceedingly expensive.

Iwafune (2000) reported learning rates of 40.8% for modular CFLs with magnetic ballasts, 15.9% for modular CFLs with electronic ballasts, and 20.1% for integral CFLs which were assumed to have electronic ballasts. While significant, the development of these learning rates, and the interpretation of the resulting values, present some challenges. Firstly, the curves are constructed only using data from four years, 1992, 1993, 1994, and 1998, and the curve fitting was assumed to maintain a constant learning rate. The range is a very narrow timeframe relative to the history of CFLs in the marketplace, and to infer a learning rate for a 1995-1997 period requires great interpolation. As a demonstration, we recreated these curves and found the learning rates for only the first three points, as shown in Figure 1. In this time frame, the learning rate appears to have an average of 36.6% with a very high correlation coefficient, as opposed to the reported value of 21.4%. One can also see the high degree of interpretation and extrapolation needed to estimate a learning reach for the entire range of production values. In addition, the mixed units on the curve (price per 1000lm vs production per unit), while understandable, result in subtle difficulties with comparing rates across datasets. For example, lumens per unit have varied over time and therefore would likely show a different cumulative production growth rate than on a per unit basis.

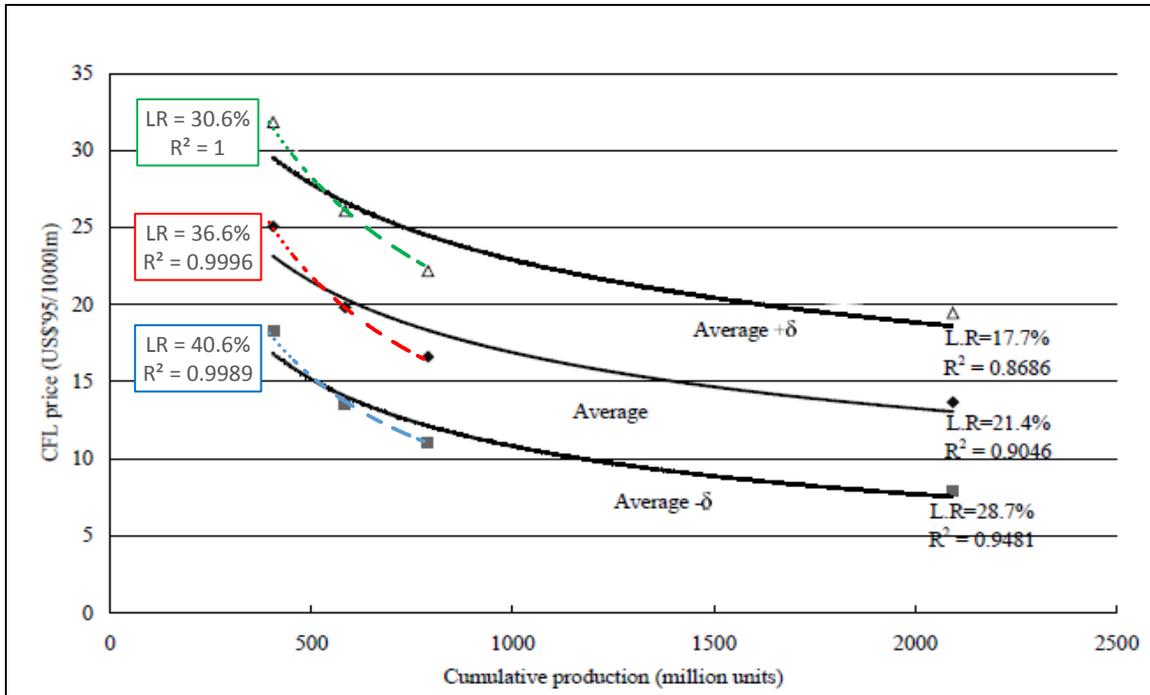


Figure 1. Variation in learning rate with one data point excluded (Iwafune, 2000)

Ellis (2006) computed a global experience curve using data obtained from the Australian Greenhouse Office (AGO, 2006) and an unreferenced source cited only as Du Pont, 2005. We have some difficulty with reviewing the resulting learning rate, owing in part to some apparent inconsistencies in interpretation of the AGO data, and our difficulty in reviewing the source literature from DuPont. For example, data from the AGO report, which is presented as annual sales, were used by Ellis as cumulative sales. Additionally, we had difficulty interpreting Ellis' resulting curve LR which he states "suggests a progress ratio of approximately 10%" and "contrasts with a value of 20.1% found in a 2000 study [by Iwafune]". Firstly, the term "progress ratio" is a well-defined term and its use here could be easily misinterpreted. Its definition should not be interchanged with the term "learning rate" since progress ratio typically refers to the percent cost remaining after a doubling in production, i.e. 100% minus the learning rate, which is the opposite of a learning rate (Taylor, 2013). If we assume the quoted progress ratio in fact refers to a learning rate of 10%, which is likely considering the comparison to Iwafune's learning rate of 20.1%, issues still remain. We gathered the data used by Ellis and plotted them in Figure 2. By our interpretation of the data, we compute a learning rate of approximately 40-45% (range given due to possible data transcription errors).

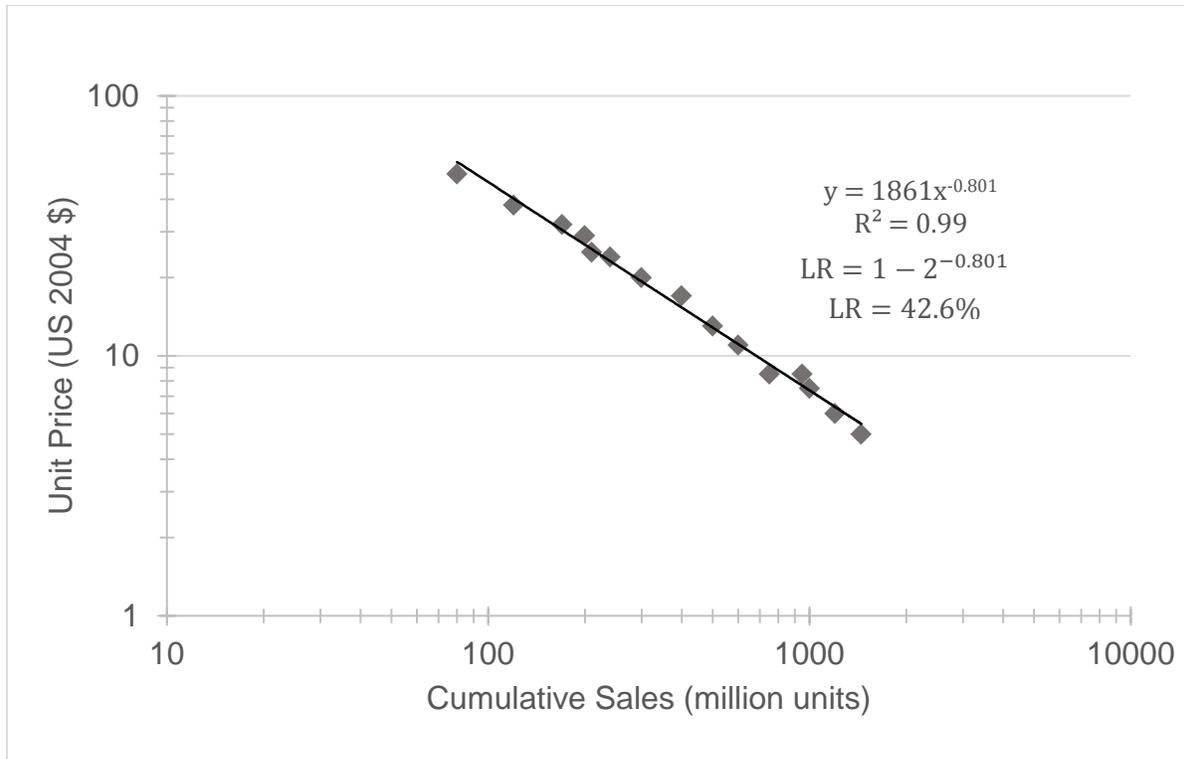


Figure 2. Global experience curve 1990-2004, recreated from Ellis (2006).

Because of the many challenges in deriving experience curves, and the wide differences in reported learning rates, we see the need for new development of the CFL experience curve that uses data thoroughly, is well-documented, covers a wide time frame, and allows for variable learning rates. In this work, we hope to reconcile the many differences in the reported CFL learning rates and present defensible and easily interpretable learning rates.

2 Issues with Experience Curve Development

2.1 Data Discrepancies

Experience curves require two datasets for a given timeframe: cost or price and cumulative production. In the absence of perfect data, information must be collected from multiple sources and processed, distilled, and combined into useful sets. For a given technology, data can be drawn from a variety of specific product types, purchasing scales, distribution channels, and geographical regions, and these details are often unreported with the data. The gathering of cost data is further challenged by confusion in whether the data report “price” or “cost” interchangeably and whether the data units (currency and year) are reported at all. Moreover, 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. These issues highlight the difficulty in determining a definitive or canonical experience curve for a

technology, since many alternative learning rates may be reasonable, depending on one's interpretation of the noisy and sometimes confused data.

These difficulties are markedly the case for deriving an experience curve for compact fluorescent lightbulbs (CFLs), because many gaps and inconsistencies are present in existing data. As such, few learning rates are reported, and mostly derived from the same few data sources listed in the previous literature section. Moreover, several reported learning rates do not explicitly reference the source data, specific product and sales conditions, or the units of the original data. A key example of this is the apparent misinterpretation of annual vs cumulative sales data between AGO (2006) and Ellis (2006). We discuss the impact of the difficulty interpreting data on CFL sales in the Methods section.

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. Experience curves depend on two datasets: (1) costs (or prices) and (2) sales. Neither of these data can be assumed to be consistent across regions, as local prices and adoption patterns often vary.

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 and political programs which contributed to development of CFLs and their market adoption. In addition, the production and trading conditions unique to the North American market for CFLs throughout the 1990's may contribute to an isolated market, particularly until 2001 when Europe placed heavy sanctions on Chinese manufacturers flooding the market at the time and the North American market did not. This factor is believed to have shifted exports of products produced in China from the European markets to the US market (PNNL, 2006). We present both curves for comparison and discussion.

Boundary selection for this work is discussed in the Methods section. Future work should further explore indicative market factors for selecting an experience curve boundary, and assess the applicability of global vs. regional experience curves.

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 (price, cost, hours of labor, etc.) and production variable (Wright, 1936), which implies that the learning rate stays constant over time. This assumption remains the prevailing approach for deriving learning curves. Alternatively, recent work by Van Buskirk et al., 2015 proposed a time-changing learning rate to help analyze the learning rates of various appliance and their markets. A non-constant learning rate allows for the possibility of noting distinct changes in a technology's development, which allows one to review existing data through the lens of time-dependency. For example, factors that affect the learning rate, such as research breakthroughs and innovation policies, may be considered.

3 Methods for Experience Curve Creation

3.1 Data Collection

We collected price data from a variety of academic journal articles and industry reports. Price data was collected on a per-unit basis, as product specifications (watt-equivalent, lumens, etc.) were not commonly available with the data collected. We also converted the data to 2004 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 Figure 3. The first two datasets, from IEA (2007) and Weiss (2007) are for the global market and are the product of many international reports and data sources. The latter four, from PNNL (2006), CPUC (The Cadmus Group, Inc., 2010), Southern California Edison (Itron, Inc., 2008), and ENERGY STAR (Bickel, 2010), are specifically for the United States and are therefore believed to be a better representation of the North American market's behavior.

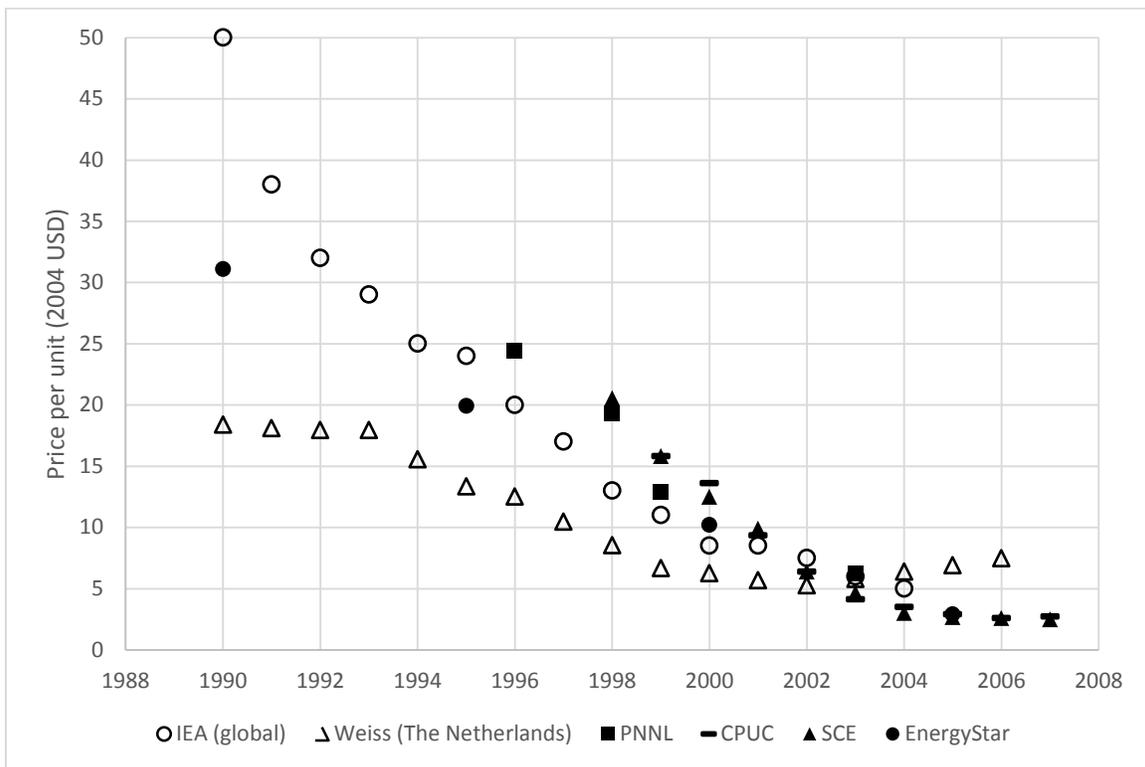


Figure 3. Aggregated price data from six sources

From these prices, we can draw a few observations. The rate of change between the datasets and across regions 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 if differences between US and global data is systematic. Overall, we see that the price of CFL bulbs have declined significantly for two decades. The exception is the data from Weiss (open triangles in Figure 3), which shows essentially no price decline from 1990-

1994, and a price increase from 2002-2006. This price behavior seems highly unlikely and is not seen in the other datasets. As a result, we chose to use Weiss data with caution in the analysis.

We compiled unit production data from three main sources of sales estimates. Iwafune (2000) presents sales by region and type (integrated or modular) from 1990-1998. Iwafune also estimates sales prior to 1990 so that cumulative totals can be computed. AGO (2006) creates a global sales dataset by pairing actual sales data from 1990-1997 with estimates based on Chinese production from 1997-2004. Finally, IEA (2010) reports annual global sales of CFLi (integrated CFLs) for 1990-2007, which closely match data reported by AGO and Iwafune, and sales by region for 2000-2007. Table 1 lists the source of data type and their characteristics.

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, 2010	Annual production	Global	1990-2007
IEA, 2010	Annual production	North America	2000-2007

3.2 Data Processing

To compute a learning rate, we combine the resulting data into two consistent datasets, one for global cumulative production and another for North American cumulative production. For global cumulative production, we averaged the reported data across Iwafune, AGO, and IEA. The resulting production curve is shown in Figure 4.

The production curve for North America required more extensive data manipulation. To compare data from Iwafune and IEA, from different time periods, we examined the percentage of global sales credited to North America. For the first section, 1990-1997, Iwafune shows North America as 25% of global sales, with a peak in 1992 (30%) and a steady decline through 1997 (to 20%). The second section, 1998-1999, there is a gap in the data. Finally, from 2000-2007, IEA shows North America as roughly 10% of global sales, starting at 7% and climbing to 15%. These values, including the 1998-1999 interpolation, are shown in Figure 5. The resulting trend appears reasonable, assuming an expected downward slope, which represents the global market growing faster than North America, and continuing through 1998-1999. The final cumulative sales curve for North America is shown in Figure 6, and again alongside the global cumulative sales curve in Figure 7.

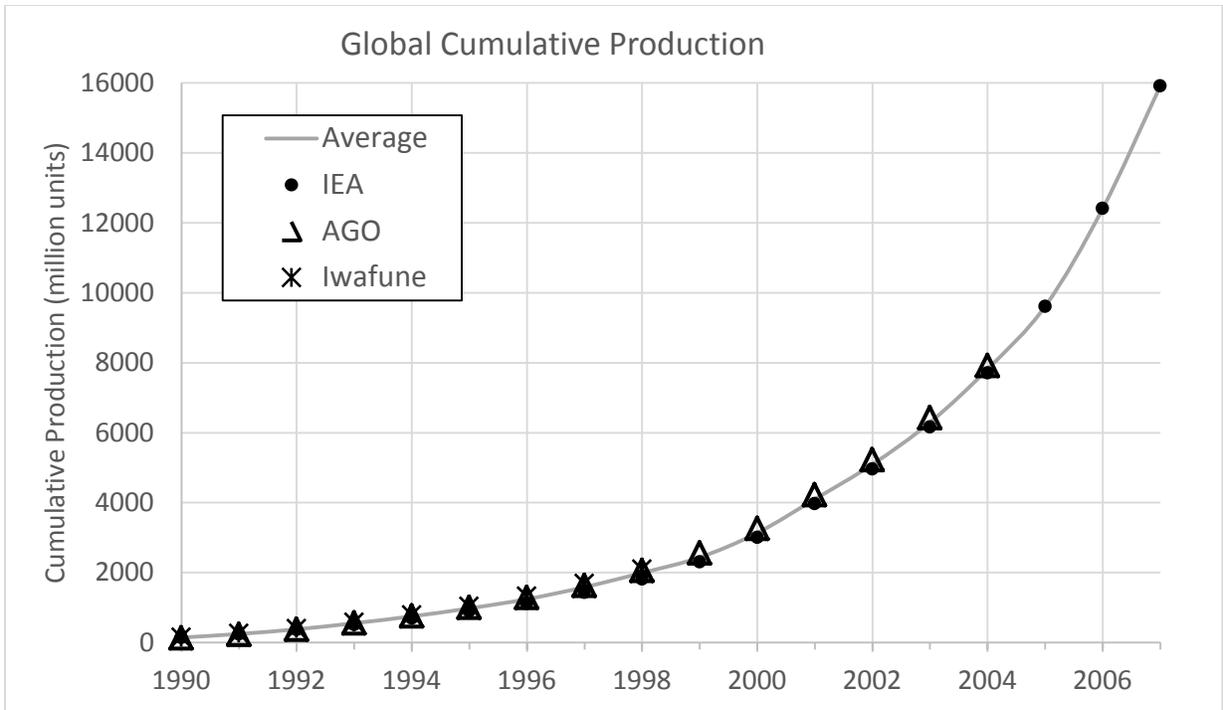


Figure 4. Estimation of global cumulative production based on three datasets

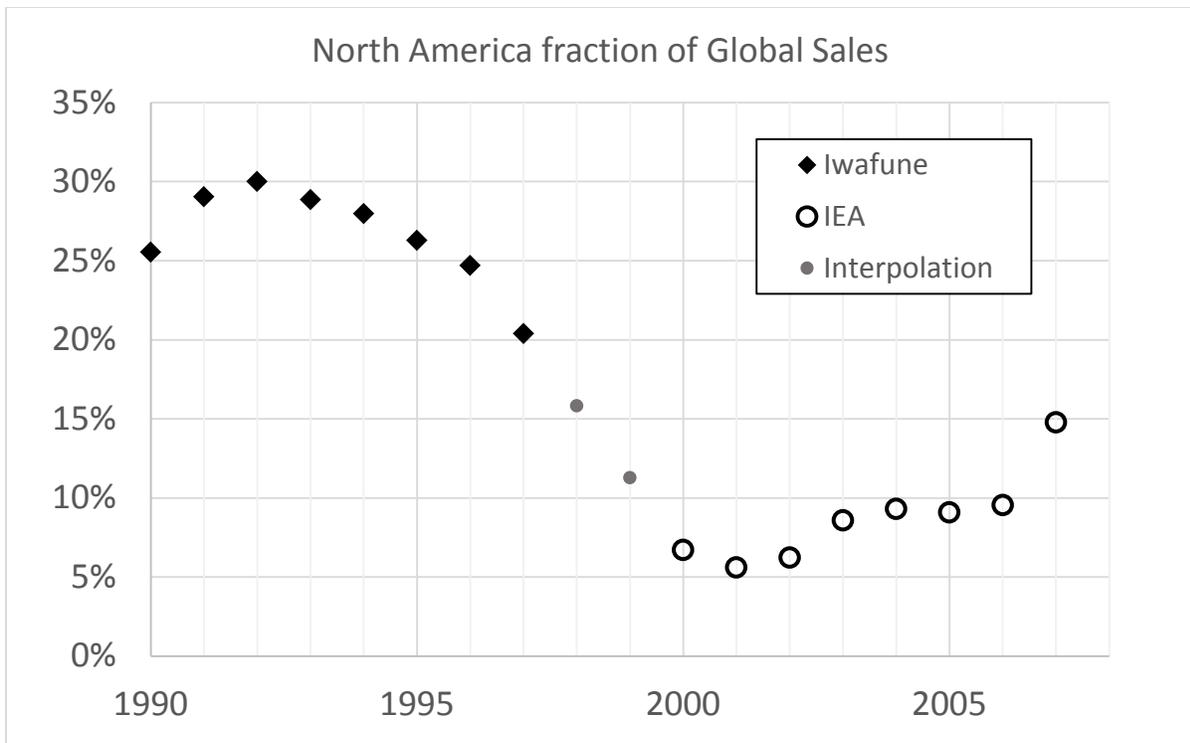


Figure 5. Percent of global annual production attributed to North America

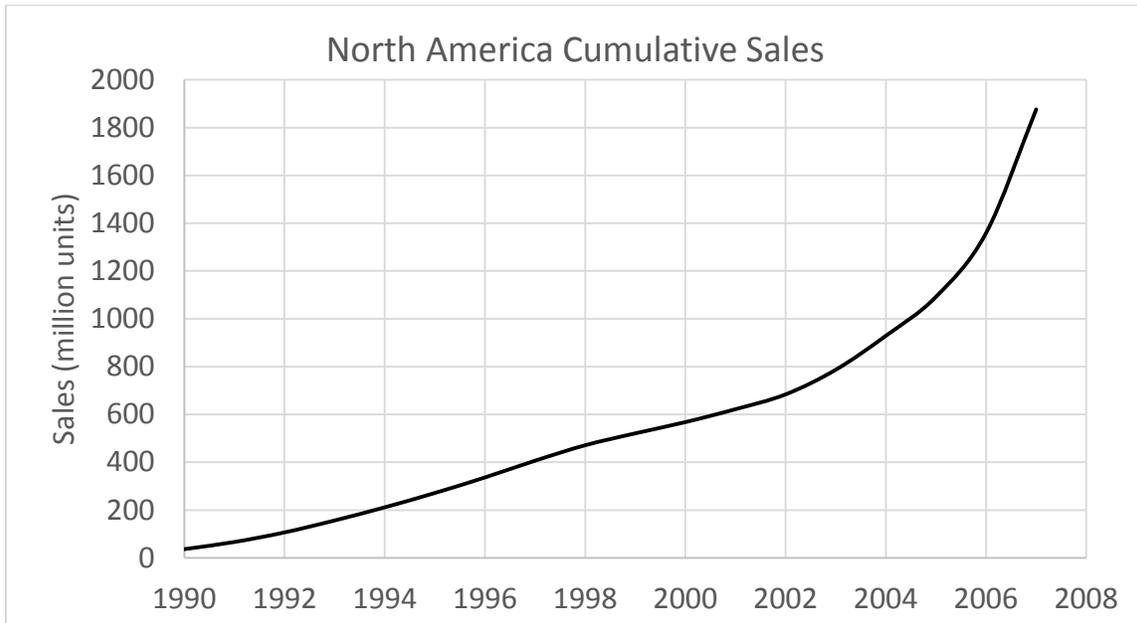


Figure 6. North America cumulative sales based on two datasets and interpolation

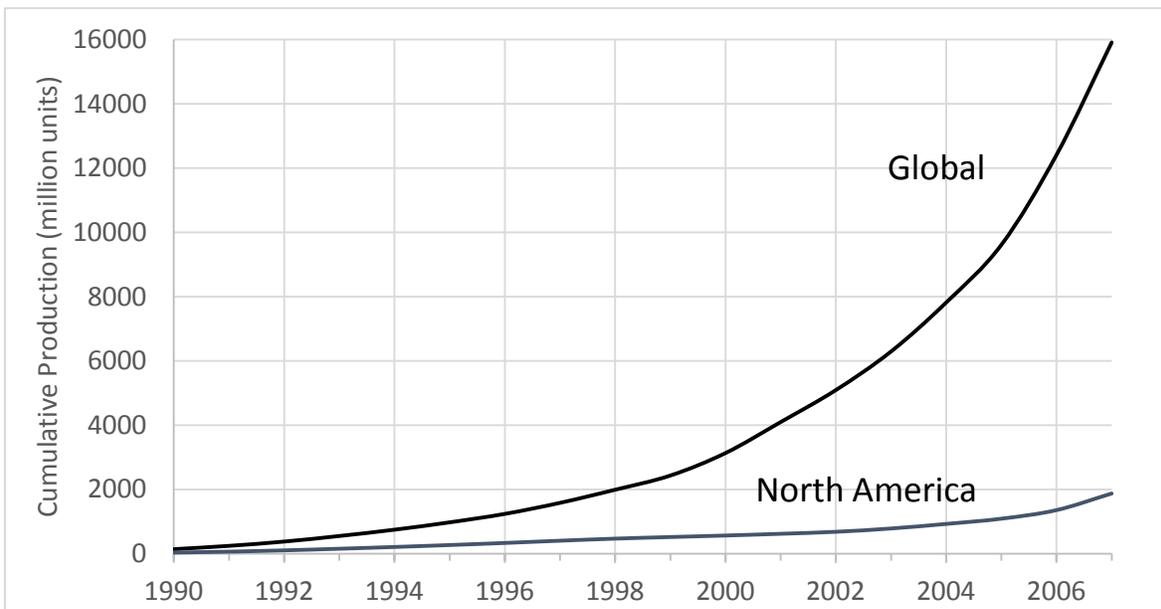


Figure 7. Global and North America cumulative production curves

3.3 Segmented Regression Analysis

Various methods can be used to determine the change, or lack of change, in the learning rate on an experience curve. In the fields of biostatistics and ecology, these methods are generally

referred to “change-point problems”. Khodadadi and Asgharian (2008) compile an extensive bibliography of these methods, ranging from maximum-likelihood estimation and Bayesian estimation to piecewise and non-parametric regression. Van Buskirk et al (2015) applied a three-equation regression fit by finding transition years that minimizes the residuals of the cumulative fit.

For our analysis, we employ a segmented regression model, which is also referred to as multiple-phase regression, piecewise regression, or broken-line regression, because it is simple to compute and interpret the curve fit. Examples of its use is presented in the context of ecological thresholds, by Toms and Lesperance (2003) and in energy analysis by Walter et al., (2014).

The general regression equation used is as follows:

$$\text{Equation 3: } Y = \beta_0 + \beta_1(X) + \beta_2(X - C)^+$$

Where:

$$\beta_0 = \text{constant}$$

$$\beta_1 = \text{slope prior to change point}$$

$$\beta_2 = \text{slope change at change point}$$

$$C = \text{change point}$$

$$(X - C)^+ = \begin{cases} 0 & \text{for } X \leq C \\ X - C & \text{for } X > C \end{cases}$$

Figure 8 shows the overall procedure for fitting a model to the experience curve data. For a given change point, C, the term (X-C)+ can be derived, and the regression problem can be solved using ordinary least squares fit. A significance test on the variable β_2 dictates to what degree a change in slope is exists. In the case of an unknown change point, a series of trial points can be tested iteratively. For this work, we used the R software program to test a range of change point locations and the presence of multiple change points. To test the possibility of the presence of multiple change points, we included an additional beta term to Equation 3 and re-computed the regression model. Finally we weighed the model fits for one-change, two-change, or no-change model based on the minimized least squared error relative to the added degree of freedom provided by additional beta term using Akaike Information Criterion (AIC) (Akaike, 1974). The MSE is not sufficient to compare across the three model types, as it will clearly improve 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. Figure 4 shows the overall procedure for fitting a model to the experience curve data.

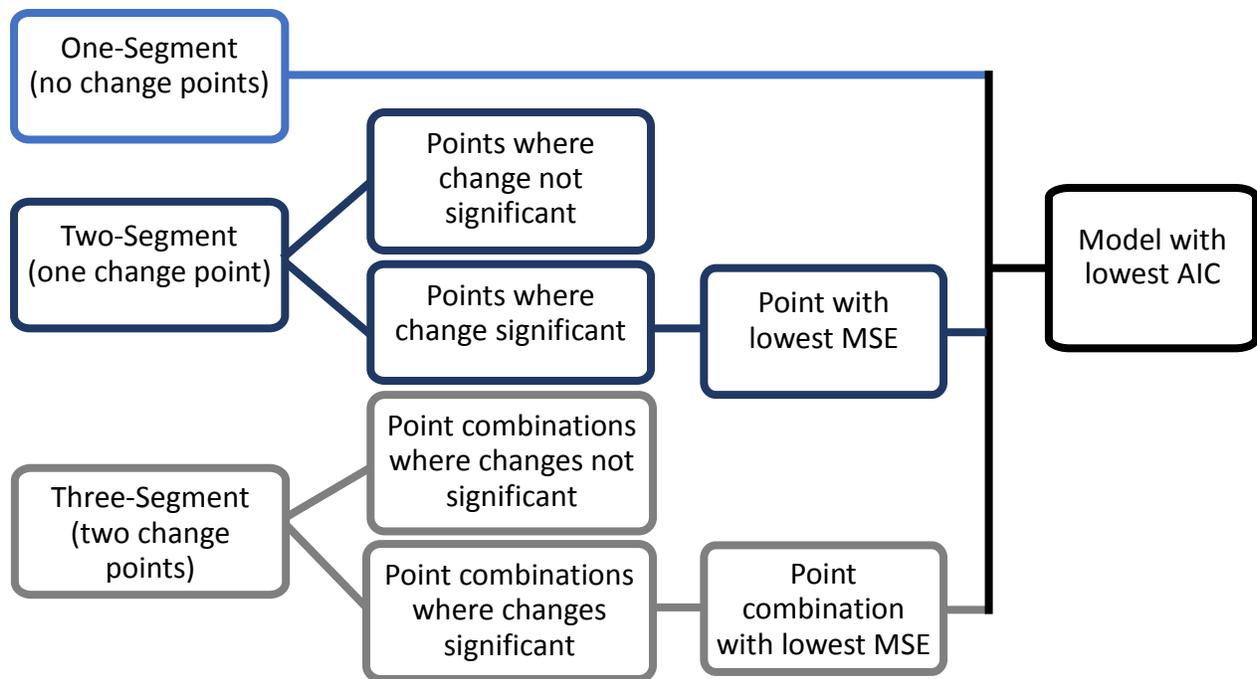


Figure 8. Flowchart for computing one- and multiple- change point models

4 Experience Curve Results

Figures 9 and 10 show the results for both the global and North America experience curves, 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. The lower the AIC, the better, and therefore the chosen models are the one-change model for the global experience curve, and the two-change model for the North America curve.

The final experience curves, shown in Figure 11, suggest interesting, while not surprising, behavior. The global experience curve shows a 20.9% learning rate from 1990-1998, followed by a 51.4% learning rate from 1998-2007. We also tested the curve including the Weiss dataset for reference, and while the learning rates differ (decreases of 2% and 7.3%), the key trend of a significant increase after 1998 remains the same. The North America market showed this trend as well, with a learning rate of 22.3% prior to, and 79.2% 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 a significant learning rate decrease after 2005, but this was not as substantially more “suitable” than the one-change model, as in the case of North America. In both curves, it is important to remember that we are viewing the changes in price over time, not manufacturing costs, so many effects beyond traditional “learning” are captured. These effects include technology advancements, profit margin reductions, and material cost decreases.

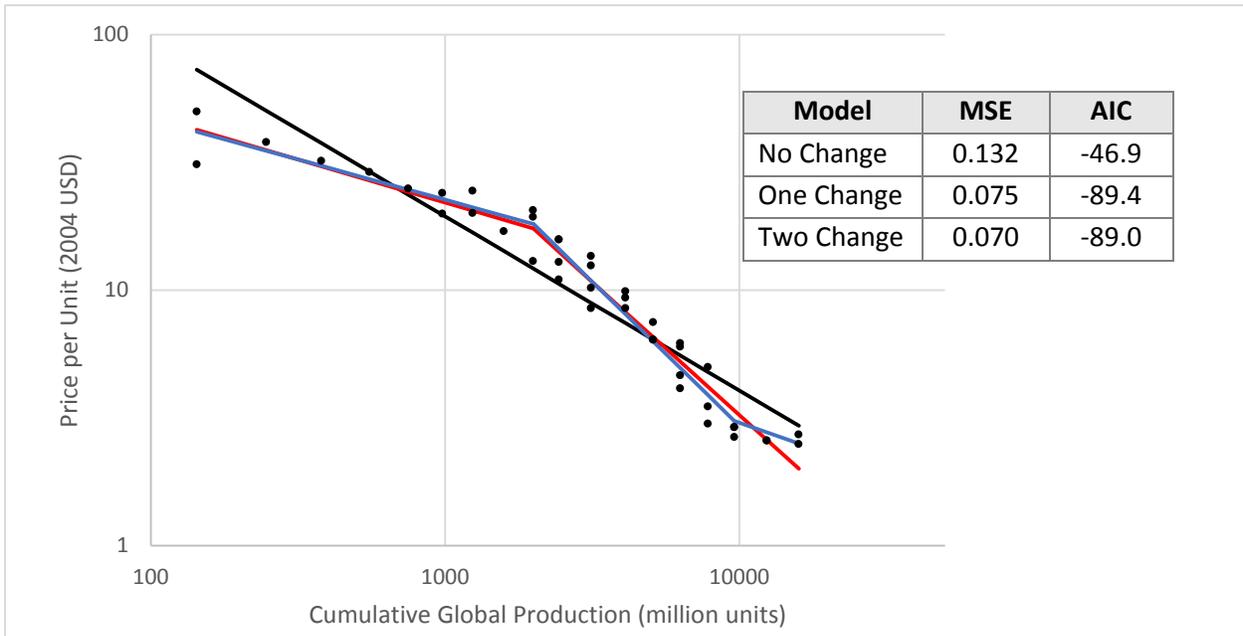


Figure 9. Global experience curves generated from segmented regression analysis

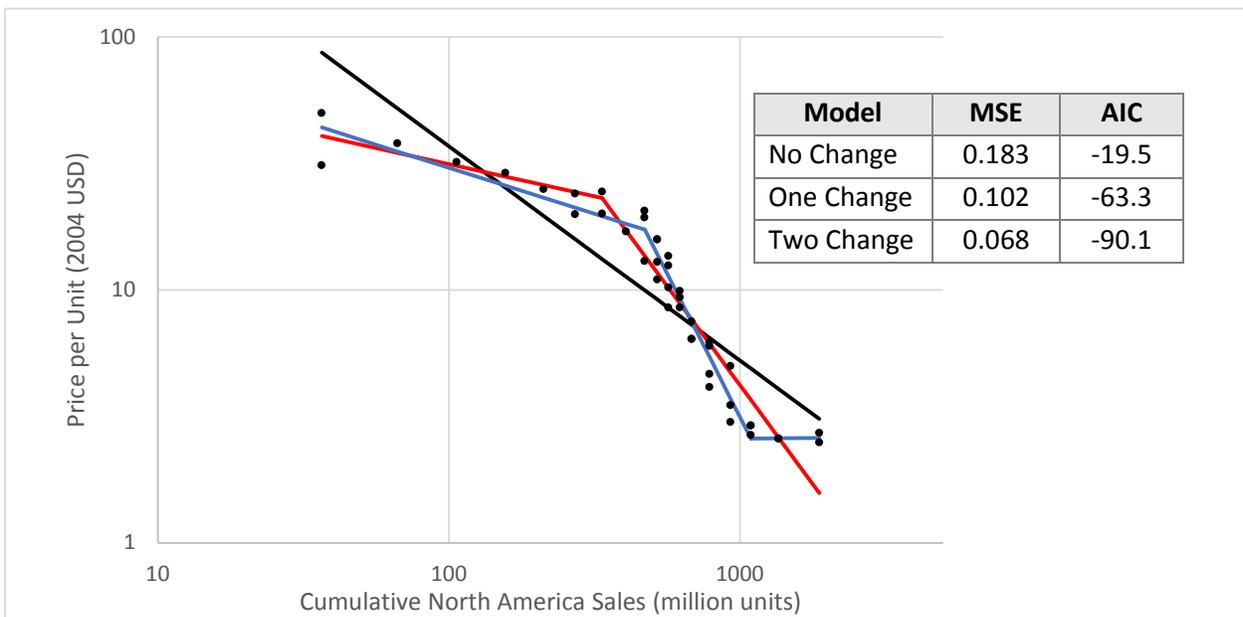


Figure 10. North America experience curves generated from segmented regression analysis

Although the proper boundaries of the CFL manufacturing system during the 1990s are difficult to ascertain, there still exists important differences in aspects beyond the factory. 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. For CFLs, we see that it varies significantly over time.

Finally, calculated learning rates for 1990-1998 align with findings in both Iwafune (2000) and Weiss (2006). Significant downturn during steady implementation of standards and programs has been seen in appliances, as previously discussed (Van Buskirk et al., 2015). Potential influences to these behaviors are discussed further in the next section.

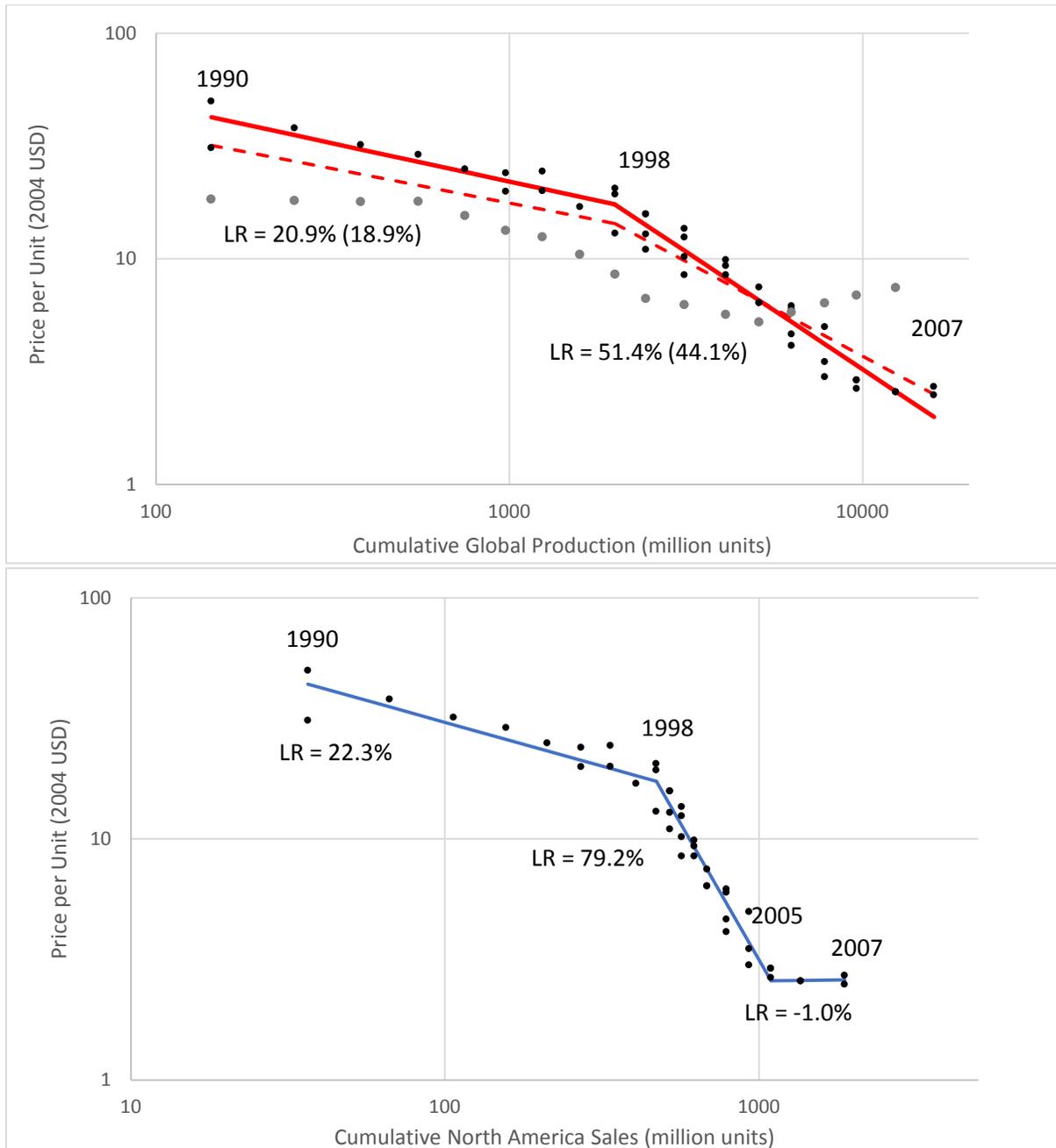


Figure 11. Global and North America experience curves. Global curve includes second case with Weiss data (grey) included (dashed line and parenthetical LRs)

5 Discussion of CFL Learning Rate Influences

5.1 Public Programs

Public deployment programs can influence a technology's advancement, and therefore learning rate, through two primary mechanisms. Firstly, by increasing adoption, programs can not only move a technology "down" the experience curve through production learning, but also induce additional progress and price savings through economies of scale and increased competition. Secondly, programs which grow a technology market can induce private research and development, either directly (through design competitions and product standards), or indirectly (through reinvestment of increased profits). This increased investment leads to design breakthroughs which improve product performance and reduce costs.

As CFL technology developed, myriad utility, state, and federal programs contributed to the development of reliable, affordable products. Some efforts have been made to link deployment programs with changes in price decline (Spurlock, 2013) and learning rate (Van Buskirk, 2015) of energy efficient technologies. However, due to the vast number and small influence area (relative to market area) of these programs for CFL technologies, it is difficult to observe the effect of any one individually.

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). The bulbs were generally promoted as a replacement for the standard incandescent lamp, which raised some issues due to early CFLs' size and performance downfalls. These programs were largely scaled back in the mid-1990s as part of large budget cuts, but some continued and even increased in scale throughout the mid-2000s.

In 1998, the U.S. Department of Energy and Pacific Northwest National Laboratory designed a technology procurement program to boost the CFL market. Through working with private multi-family housing owners (PMFOs), DOE identified integral CFLs (those not requiring pin-based fixtures) as a low-cost, low-risk technology that could gain wide adoption by owners. The primary market barriers in integral CFL adoption were identified as price and size, which therefore led to the creation of a design and procurement program for new "sub-CFLs" (Ledbetter, 1999). Through this program, DOE aggregated buying power from multiple PMFOs to express demand for these products, and sold successful designs through a dedicated online retail channel. Successful designs were those that met a variety of performance and energy criteria, and most importantly, fit size requirements that enabled them to fit anywhere a standard incandescent could. The program was successful, with sales greatly exceeding expectations and 16 new models were brought to the market by the three participating manufacturers. In addition,

similar products were introduced by non-participating manufacturers shortly after, and these products began to be sold through multiple retail channels.

ENERGY STAR launched its specification for residential light fixtures in 1997, and for CFL bulbs in 1999. As the first national effort to increase CFL adoption, the program qualified almost 200 models from 10 different manufacturers in its first year, growing to 1,600 models from 100 manufacturers in 2010 (Bickel 2010). Requirements for ENERGY STAR set the first benchmark for energy efficiency, light quality, and product performance in CFLs while also focusing on testing procedures. These standards brought higher-quality products on the market, increasing consumer satisfaction and, therefore, adoption (EPA, 2012). Shortly following the creation of requirements, the 2001 nationally coordinated lighting promotion, “Change a Light, Change the World” educated consumers and promoted CFL technology, furthering the program’s impacts.

These factors are related to our resulting experience curve plots in the sense that they have an influence on both production rates and price reductions. Production rates are driven by customer demand, and programs which promote CFLs to the public, offer incentives, and influence product quality will all increase demand, which in turn decreases cost through economies of scale and technology learning. Meanwhile, programs which promote innovative design, higher performance metrics, and manufacturer investment incentives will initiate technological advances which may further reduce cost. In the Discussion section (V), we discuss how these impacts are likely to have resulted in the learning rates seen in this work.

5.2 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), when modeling factors influencing the cost of photovoltaics, found factors such as 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. They found that products can often be described in the experience curve context as the sum of a component that experiences learning (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, each learning at a different rate (one, for which, may be zero), yields a better fit than 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 one component (the ballast) which has undergone significant learning 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). These ballasts demonstrated learning rates of 8% from 1986-1991 and 23% from 1992-2005 (Wei et al. 2015a). Future work should further explore the relationship between these two technologies and determine the extent to which ballast cost reductions account for CFL cost reductions over time.

5.3 External Events

Many other factors, outside of the CFL market and deployment programs, likely influenced the technology's development pattern. Electricity prices are often a driver for adoption of energy-efficient technologies, as they make them more financially viable to consumers and generally raise awareness of energy consumption. Although they do not necessarily have an 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. Similarly, discrete events such as the western electricity crisis of 2001, can spark product development through creating demand for efficient products, increasing market competition, and triggering deployment programs.

Market competition in CFLs was also driven by a shift to production in low-income regions such as China (Weiss, 2007). 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 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, 2007).

6 Discussion of Results

6.1 Program Correlation

Many of the programs and events discussed in the previous section correlate to the sustained downturn seen in the experience curves. These are shown in Figure 12. As shown, the increased slope occurs after substantial technology developments had occurred in the sub-CFL procurement program, and during the time that ENERGYSTAR standards are active. These programs, along with the external events happening at that time, created a recipe for accelerated development. The relationship between these programs and the experience curve is important for both historical and projection analyses. 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 the impacts of the programs and events that are likely to occur (or end) during the time frame of interest can help inform how the experience curve will behave.

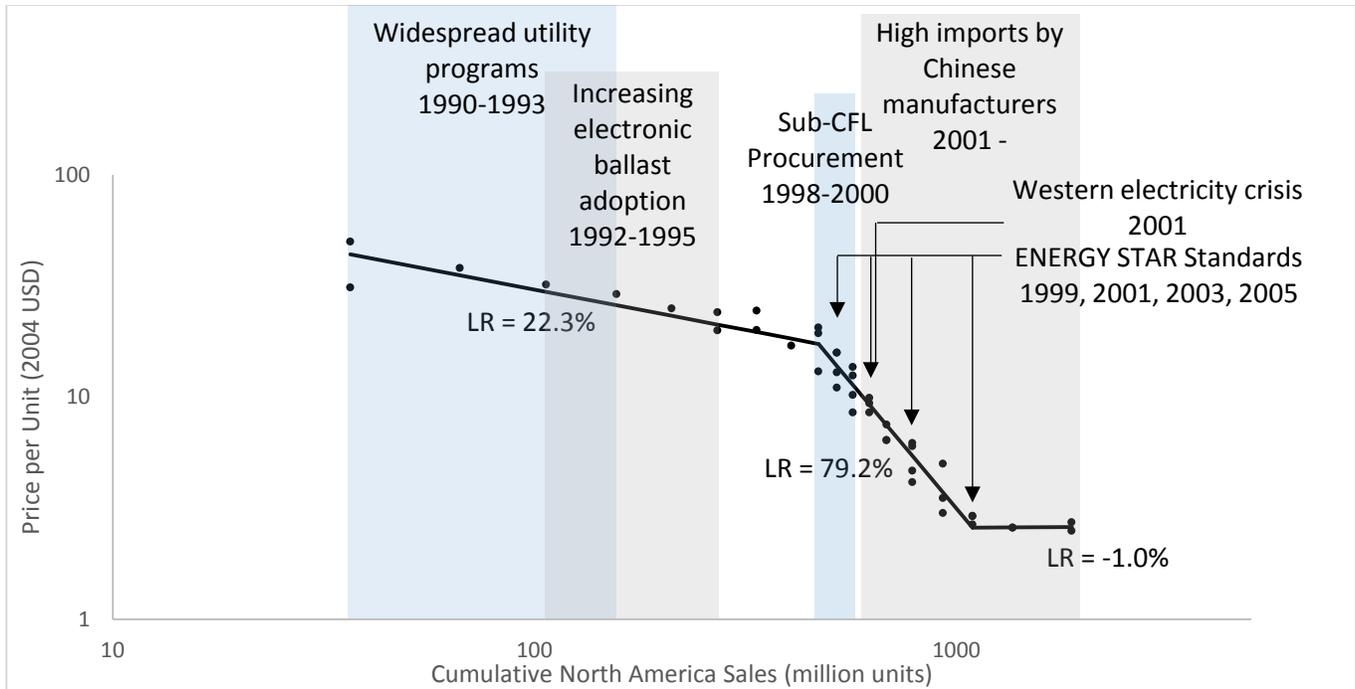


Figure 12. North America experience curve and influencing factors 1990-2007

6.2 Global vs. North America

Although the global and North America experience curves generally show the same patterns, there are substantial differences, particularly after 1998. North America shows a significantly higher learning rate (~80%) than the global rate (~50%), which is not unexpected in a truly global economy. In the case where all units are manufactured on a global market, and cost reductions occur at the manufacturing level, the North America curve would be expected to show an increased rate, as the cost reductions are due to much higher (global) levels of production. While the North America curve may not be truly representative of the CFL market, particularly in later years, it can provide valuable insights to trends such as the flattening out of the curve from 2005-2007. This result draws further attention to how closely the one-change and two-change models performed in the global case. While the choice between the two models may not be as significant for retrospective analysis, it would have an extremely significant effect on price predictions after 2007.

Other technologies may benefit more from regional analyses than CFLs. For example, examining newer technologies that are manufactured in isolated markets can provide counterfactuals for program analyses or insight for improving learning rates in certain regions. This is not as possible in the case of CFLs, where regional markets are not isolated, but a subset of the larger global market. Further research should examine the relationship between experience curves for branches of a technology's market, where different adoption curves are relevant at different points in the supply chain.

6.3 Implications for Historical Analysis and Forecasting

Historical CFL experience curves provide valuable insights for understanding the development of the technology. As shown, CFLs demonstrated a steady sustained learning rate of ~20% through the 1990s, then significantly increased from 1998-2005. This information may be used to assess the impacts of various programs occurring during that time by analyzing the cyclical benefits of increasing adoption, which leads to cost reductions, which leads to 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 be largely due to economies of scale and manufacturing efficiency improvements, while in the 2000s may have a larger component be due to decreases in profit margins. Methods to disaggregate these price reductions are further explored in another report (Wei, et al. 2015b).

The CFL experience curve can also be used as a means to forecast future technology development and inform policy and program planning. The benefits that support program spending are often dependent upon a certain level of technology adoption, which is directly tied to cost reductions. The experience curve is a means to understand current cost trends which can inform projections of cost and therefore adoption. In this study, the variations in the two- and three-segment experience curves provides particularly interesting results for this purpose. 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 may have been reached. These different trajectories from 2005-2007 would result in vastly different results if projected forward. Further data collection would be needed to determine if this flattening of the experience curve is a sustained change beyond this time period. Using these possible scenarios in policy planning is useful to account for the many uncertainties surrounding technology development. Beyond choosing which model to project, one must also consider the possible variations in future trajectories in the case that another change in the learning rate occurs. While this may increase uncertainty in projections, it can more comprehensively capture the range of likely scenarios.

Lastly, this work can inform future decision-making regarding new, similar technologies. For example, other lighting technologies such as LED will need to experience substantial cost reductions before they are competitive with incumbent technologies. Knowledge about not only the learning rate demonstrated by other lighting technologies (CFLs), but also what led to those learning rates, is useful in predicting what range of learning rates LEDs may experience. This knowledge can also demonstrate 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.

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