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Equipment Price Forecasting in Energy Conservation Standards Analysis

Comments submitted to the US Department of Energy

On behalf of the Natural Resources Defense Council and the Appliance Standards Awareness Project

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1. Executive Summary

This paper was prepared by Synapse Energy Economics[1] for the Natural Resources Defense Council and the Appliance Standards Awareness Project in response to the U.S. Department of Energy's (DOE) request for comments on *Equipment Price Forecasting in Energy Conservation Standards Analysis*, Docket No. EE-2008-BT-STD-0012.[2] The DOE has proposed the use of a learning curve model to forecast the future costs of technologies that could be used to comply with energy conservation standards. These comments provide an overview of how the learning curve model has been applied in general; a discussion of how learning curve analyses have been applied to energy technologies; and an analysis of how learning curves can assist with forecasting the costs of refrigerators and freezers.

A brief review of the relevant literature indicates that the application of learning curves is a widely accepted and sound approach to analyzing and forecasting product prices. It has been used to explain declining prices trends for a variety of products, ranging from Ford Model T's, to airplanes, to computers, as well as electricity generation technologies and electricity end-use equipment.

The DOE NODA refers to a companion paper, *Using the Experience Curve Approach for Appliance Price Forecasting*, February, 2011, which presents a summary of data and literature relevant to learning curves for several electricity and natural gas end-uses.[3] We find that the learning curve model presented and applied in this paper offers an analytically sound and appropriate methodology for the DOE to use in forecasting future prices of energy end-use equipment.

In Section 4 below, we apply the learning curve model to refrigerator and freezer products, using the data and methodology outlined in the *Experience Curves* paper. Our analysis indicates that (a) there is sufficient data available to apply the learning curve model to refrigerators and freezers separately; (b) the learning curve model results in learning rates for refrigerators and freezers that demonstrate a very good fit to historical data; and (c) this model can and should be applied to forecast costs of refrigerator and freezer products.

Historic cost trends clearly indicate that electricity end-use products have experienced significant reductions in costs over time, and there is no evidence to suggest that such cost reduction trends will abate in the future. Accordingly, we support DOE's proposal to apply the learning curve concept in its analysis of energy conservation standards, and we support the specific learning rates presented in the *Experience Curves* paper.

The historic evidence of price reduction trends is so clear that the DOE should always use some form of learning curve approach in forecasting future end-use costs – either the

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1 Synapse Energy Economics is a research and consulting firm specializing in energy, economic and environmental topics. We apply analytical tools to complex resource and policy questions. Our work is typically presented in testimony or reports that are intended to inform sound decisions with regard to ratemaking, regulations, planning, operations and policy. See www.synapse-energy.com.

2 76 Fed. Reg.9696 (Feb. 22, 2011). We refer to this document throughout as Notice of Data Availability and Request for Comments (NODA).

3 We refer to this paper throughout as the *Experience Curve* paper.

learning curve model or some more simple proxy – unless there is clear evidence that historic cost reduction trends will be reversed in the future.

In its NEMS modeling the EIA has clearly acknowledged the importance of accounting for learning curves in forecasting future costs of generation technologies. Since the NEMS model is used by the DOE to forecast retail electricity prices that are used in evaluating energy conservation standards, it is essential that the DOE account for learning curves in forecasting the future costs of demand-side technologies. Otherwise, the DOE analysis will contain an inherent bias against demand-side technologies and against the energy conservation standards.

Finally, the NODA indicates that DOE is considering a consumer surplus framework as an alternative to the current life-cycle cost framework for evaluating energy conservation standards. We have several concerns about this alternative framework: it is not representative of energy products and services that face a number of market barriers; it requires the use of customer demand curves that are very difficult to develop for energy products and services; it is not transparent or accessible to policy-makers; and it requires data that are not easily available.

2. General Application of Learning Curves

The Learning Curve Model

Our review of the relevant literature indicates that the application of learning curves, or experience curves, is a widely accepted and sound approach to analyzing and forecasting product prices. The learning curve is an empirical model that fits historical cost or price data to the cumulative production of the appliances. Technological learning is typically analyzed using the following model:

$P(X) = P_0X^{-b}$, (1)

where P is the price and/or cost data, P_0 is the price and/or cost of the first unit of production, X is cumulative production, and b is the learning rate parameter.

The percentage reduction in cost and/or price that occurs with each doubling of cumulative productions is called Learning Rate (LR) and is calculated as follows:

$LR = 1 – 2^{-b}$ (2)

For instance, LR=0.2 implies that doubling of the product’s cumulative production reduces its cost by 20%.

The learning-by-doing phenomenon was introduced by T.P. Wright in 1936 when he suggested a relationship between man-hours required to assemble successive airplane bodies as he observed a constant linear reduction in man-hours needed every time the total number of airplane bodies doubled. In other words, Wright suggested that the amount of man-hours, or input, declines by a constant percentage as the total output of the product doubles. This percentage decline in costs and/or prices is usually referred to as the Learning Rate (LR).

Since the introduction of learning-by-doing in the 1930s, this model has been applied to a wide range of industries, technologies and end-user products. For instance, Laitner and Sanstad (2004) summarize applications of the learning curve model to a number of technologies, including scrubbers, photovoltaics, and even the Ford model T auto, and report learning rates for these technologies between 0.03 and 0.33. The *Experience Curve* paper applies the learning curve model to selected end-user durable goods and finds learning rates between 0.13 and 0.53. Table 1 below provides learning rates for several goods and technologies. It is noteworthy that freezers and refrigerators are among the products with the highest learning rates, with refrigerators competing in learning rates with computers.

Table 1. Examples of Learning Rates for Selected Technologies and Goods[4]

Technology	Learning Rate
Magnetic Ballasts	0.03
CFC Substitutes	0.07
Scrubbers	0.11
Electronic Ballasts	0.12
Ford Model T Auto	0.13
Gas Water Heaters	0.13
Electric Water Heaters	0.17
Unitary AC	0.18
Photovoltaic Cells	0.28
Integrated Circuits	0.33
Freezers	0.38
Room AC	0.40
Clothes Washers	0.42
Computers	0.51
Refrigerators	0.52
Compact Fluorescent Light Bulbs	0.53

The Learning Curve Concept Applied to Energy Technologies

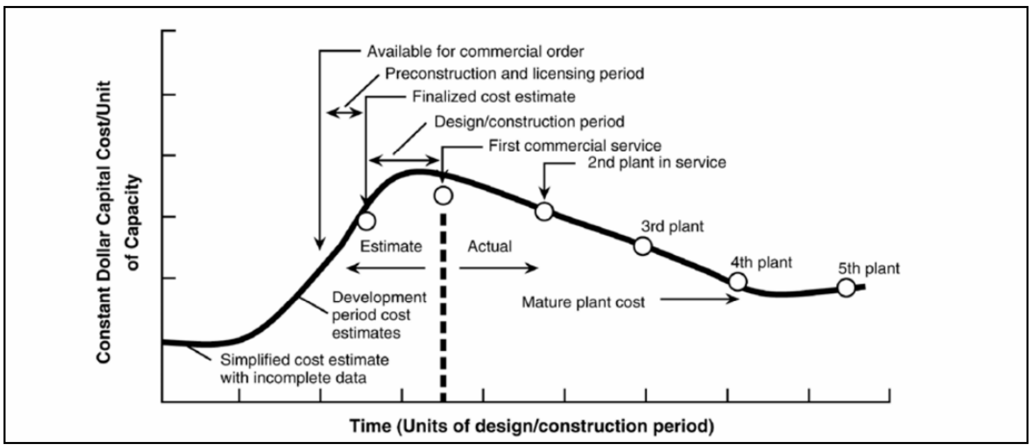
Jamasb and Kohler (2007) provide a summary of existing literature quantifying learning effects in the energy sector, with a focus on electricity generation technologies. They show that the estimates of learning rates associated with different technologies and different time span (dating back to 1980) range from 0.03 to 0.35. This learning rate literature has even defined a general “rule of thumb” learning rates of 20% as a proxy rate for many electricity generation technologies. Jamasb and Kohler (2007) have also analyzed applications of the learning curve to a low-carbon electricity sector. They conclude that even though most low carbon technologies are more expensive than current dominant technologies, these low carbon technologies will become cheaper faster than current technologies.

4 Sources of data in the table: Laitner and Sanstad (2004), The *Experience Curve* paper.

Technological learning has been widely recognized and accepted in the literature analyzing non-fossil fuel energy resources. Wene (2000) presented estimates of learning rates for electricity generating technologies, such as photovoltaics, wind, district heating and natural gas combined cycle. Muller-Furstenberger and Stephan (2007) suggest a learning rate of 18% per doubling of installed capacity in non-fossil fuel energy supply as a reasonable average of empirically observed learning rates. Junginger et al. (2005) perform an experience curve analysis for the wind farms and find an average wind farm learning rate of 19%. They report that combined with various growth scenarios for global wind capacity, such learning rates will result in cost reductions of 43-75% by 2020 compared to the current wind farm construction costs . With such adjustment to wind costs, a large fraction of electricity from wind may be able to compete with electricity from conventional fossil fuels by 2020.

The phenomenon of technological learning during transformation of technology from its commercialization stage to maturity is also acknowledged and modeled by Electric Power Research Institute (EPRI)[5]. EPRI (2009) shows that in the case of capital costs, costs increase exponentially at the development stage before commercialization of technology; once technology is in commercial service, capital costs start declining gradually due to learning, as shown in Figure 1 below.

Figure 1. EPRI Capital Cost Learning Curve



EPRI (2009) describes a number of uncertainties, including technical, estimation, economic, and other, that cause capital cost to vary among technologies and among projects in the power generation sector. Quantifying these types of uncertainties is necessary in developing cost estimates. Although technological change is only one of many uncertainties that may affect capital cost of a technology or product, modeling technological change through technological learning models is a good first step in accounting for these uncertainties.

While considerable attention has been paid to the learning rates of supply-side options, until recently less attention has been paid to learning in the context of energy demand technologies. Bass (1980) estimated learning rates for some energy-using consumer durables, such as air conditioners, dishwashers, refrigerators and televisions, to be between

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5 See EPRI (2009) for impact of learning on capital costs.

0.1 and 0.4. Similar results were presented by Newell (2000) who estimated learning rates for room and central air conditioners of approximately 0.4.

Laitner and Sanstad (2004) and Watanabe (2002) analyze learning curve models and show that ignoring technological learning on the demand side introduces biases in the analyses of energy-related technology as production of energy-consuming durables has significant potential for cost reductions due to technological learning. They perform a simple analysis in which learning-by-doing is simultaneously represented on both the supply and demand sides of the electricity market. They find that under the assumption of no learning and no energy efficiency, 82% of total electricity demand is met by existing technologies (technologies similar to those existing in 2002) by 2032, which results in total electricity expenditures of $430 billion in 2032. With learning only included on the supply-side, the share of existing technologies in meeting total demand declines to 56% and total electricity expenditures drop to $390 billion in 2032. With learning both on the supply side and demand side, market share of existing technologies declines further to 39% and the nation's total annual electricity bill decreases to $286 billion.

Advantages and limitations of the learning curve model have been discussed widely in the literature. Weiss (2010) provides a detailed discussion of model limitations and other factors affecting prices and/or costs of appliances that are omitted in the model. Laitner and Sanstad (2004) acknowledge learning curve model limitations but show that controlling for technological learning even in such a simplified form consistently results in more accurate cost forecasts than those produced with current assumptions about technology.

The Learning Curve Concept as Applied in NEMS

Every year EIA produces a long-term analysis of the U.S. energy market, presented in its Annual Energy Outlook (AEO) report. This annual report is based on the long-term projections generated by the National Energy Modeling System (NEMS); a model of energy economy equilibrium that projects supply, demand, new capacity, energy prices, emissions and other parameters of energy markets. Currently, EIA recognizes the impact of technological learning on its projections of costs of technologies but only on the supply side of the energy market. [6]

As discussed in Gumerman et al. (2004), technological learning in the NEMS model is expressed as a percent reduction of overnight capital costs. It is introduced into the model via two parameters: Learning-by-doing rate and technological optimism rate. Learning-by-doing rate is a measure of cost decline as output of a product increases and a firm accumulates experience with its production (applies to all incremental construction). Technological optimism rate measures cost decline due to learning associated with initial commercialization of electric generating plants, and applies to construction of the first 5 plants of any technology type.

6 See Gumerman et al. (2004) for more details on learning and cost reductions in NEMS.

NEMS assumes three stages of technological development – revolutionary, evolutionary, and conventional.[7] NEMS associates each technological stage with certain values of learning rate, as shown in Table 2 below.

Table 2. NEMS Learning Parameters for Each Technology Classification[8]

Vintage	Learning Rate[9]
Revolutionary	10%
Evolutionary	5%
Conventional	1%

NEMS incorporates technological learning rates into its projections for all new and emerging supply-side technologies, with a particular focus on electricity generating technologies.

Among other NEMS modules, the Oil and Gas Supply Module explicitly models advanced production and processing operations to determine the impact of technological change on supply, reserves, and other economic parameters of the oil and gas market.[10] Similar to any other technology, oil and gas supply technologies will not be implemented unless the benefits from this technology are greater than the cost to apply it.

In its NEMS modeling the EIA has clearly acknowledged the importance of accounting for learning curves in forecasting future costs of generation technologies. Since the NEMS model is used by the DOE to forecast retail electricity prices that are used in evaluating energy conservation standards, it is essential that the DOE account for learning curves in forecasting the future costs of demand-side technologies. Otherwise, the DOE analysis will contain an inherent bias against demand-side technologies and against the energy conservation standards.

3. Review of the "Experience Curves" Paper

The *Experience Curve* paper provides a useful assessment of the potential for applying learning curves to appliances and equipment. However, the value of the learning curve approach will depend upon the quality of the underlying data available, and thus the approach cannot be applied without a thoughtful analysis of the relevant data.

First, it is important to assess the quality of the data on price and production. The *Experience Curve* paper uses product-specific producer price indexes (PPI) from the Bureau of Labor Statistics (BLS) as a proxy for product-specific price data. PPI data for "Household refrigerators, including combination refrigerator-freezer" are available for every year between

7 These three stages, or "vintages", roughly correspond to the three stages of technological development proposed in Grubler et al. (1999) – radical, incremental, and mature, respectively. Mature technology is the one that saturated the market and has limited potential for cost reductions due to learning. Incremental technology has substantial market share and potential for significant cost reductions due to learning. Radical technology has almost no market share and may never reach any significant commercialization, but has the largest potential for cost reductions due to learning. For more discussion on technological stages, see Gumerman et al. (2004) and Grubler et al. (1999).

8 Source of the table: Gumerman et al. (2004).

9 Learning Rate in NEMS model is calculated in accordance with its generally accepted definition: $LR=1-2^{-b}$, where b is the parameter estimated empirically in the learning curve model.

10 Information on NEMS Oil and Gas Supply Module is available at http://www.eia.doe.gov/oiaf/aeo/assumption/oil_gas.html

1976 and 2009. PPI data for “Household food freezers, complete units”, used for calculation of freezers learning rates, are only available for 1989-1993 and 2003-2009. Shipments data used in the analysis are collected from a list of data sources similar to the ones reported in the NODA. Historical shipments data for refrigerators and freezers goes back to 1951. Future DOE projections up to 2043 are also available.

The lack of pricing data for the early stages of refrigerator and freezer development (1930s – 1970s) and gaps in existing data suggest the need for careful application of the model to the data and thoughtful interpretations of model projections.

Second, to make conclusions about the validity of the learning curve model, it is important to determine whether application of the model to the data results in a statistically significant fit. This should be investigated by applying the model to historic prices and production levels. We have applied the learning curve model to the data sets described in the *Experience Curve* paper, and obtained very similar learning rates. After fitting the model to the data we can conclude that the model produces a very good fit of estimated prices to the available historic price data. This indicates that the model may be suitable for projecting future prices. The details of our analysis replicating results of the paper are provided in the next section.

Third, although we believe that the proposed methodology is a good first step to improve the analyses for efficiency standards rulemakings, it is important to acknowledge other factors that might explain variation in prices. The most common concerns with the model cited in the literature include:[11]

a) Use of appliances' average *prices* as a proxy for their *costs* in learning curve analyses. Average price is a good proxy for costs only if price-cost markups are constant over time. Use of price as an imperfect proxy for costs introduces time dependency in the model since the price is also dependent on overall increases/decreases in input costs, other production costs, or other overall changes in the industry over time. A way to acknowledge this is to control for a time trend in the model. But overall, under conditions of competitive markets for refrigerators and freezers, bias from using prices as a proxy for costs is not substantial as the competitive profit margin is not very large.

b) Other factors influencing appliances’ production costs, such as cumulative investment, R&D, knowledge stock, economies of scale and scope, technological spillover, or technological learning in other industries and improvements in ancillary technologies.

c) Constant learning rate, predicted by the model over time. The learning curve model implies that at the different stages of technological development, equipment costs and/or prices decline at a fixed rate every time the cumulative output doubles, while the absolute reduction may be very different at different stages of the learning curve. However, some argue that production costs may decline at different rates every time the output of a product doubles.

Estimating costs as a function of only cumulative production, therefore, creates a problem of omitted variables. And although cumulative production might be the best proxy for all above mentioned factors, omission of those factors could introduce bias into the learning curve

[11] Weiss et al. (2010)

model. It is very difficult to control for those possible effects due to lack of data, but it is important to acknowledge them when interpreting the results of learning curve analysis.

Overall, we believe that the approach recommended in the *Experience Curves* paper is appropriate, although some thought must be given to what data are available and how to apply the results. DOE's current assumption that "the manufacturer costs and retail prices of products meeting various efficiency levels remain fixed, in real terms, after the compliance date and throughout the period of the analysis" [12] may significantly overestimate long-term prices and costs as real costs and prices of appliances tend to decrease over time due to accumulated "learning" or "experience" in production. The proposed methodology is a sound first step in the direction to more accurate and robust cost estimates. Existing literature and research on this issue indicates that inclusion of technological learning consistently results in more accurate estimates of costs than those produced with DOE's current approach to long-term price and/or cost trend forecasting.

4. Application of Learning Curves to Refrigerators and Freezers

Refrigerators and Freezers Combined

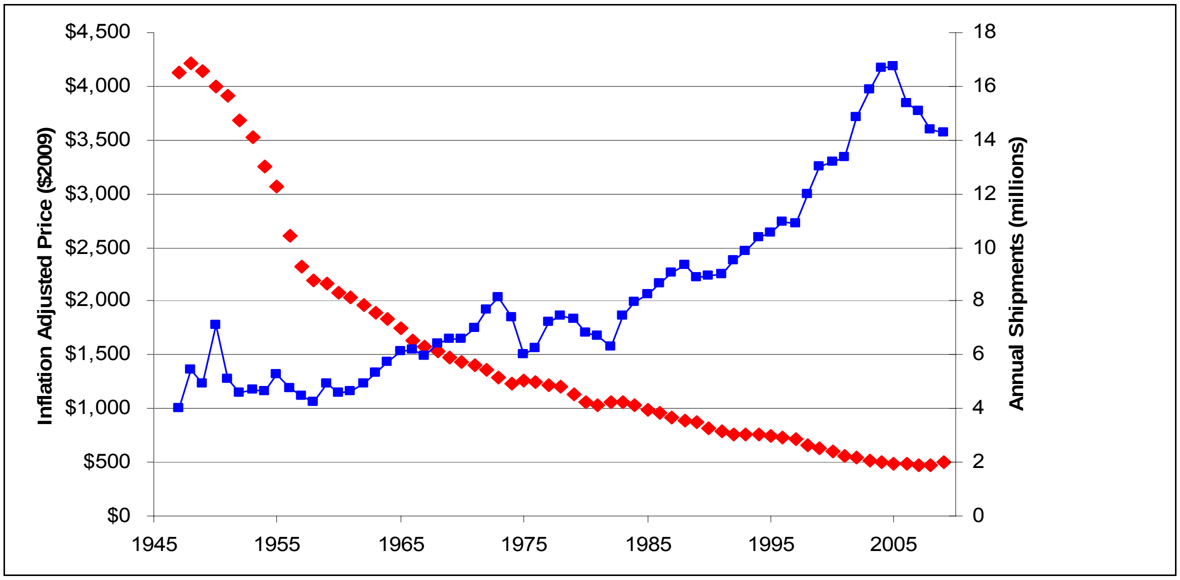
In its Notice of Data Availability (NODA) suggesting changes to the approach for estimating future compliance costs of efficiency standards, DOE provided aggregated annual historical data on inflation-adjusted prices and shipments of refrigerators, refrigerator-freezers and freezers for the period of 1947-2009. We use these data to analyze historic learning curves, calculate learning rates, and evaluate the opportunities for applying the learning curve methodology to refrigeration products.

Figure 2 below illustrates an overall increasing trend in annual shipments and a consistently decreasing average annual price of refrigeration products between 1947 and 2009. It is clear from the graph that refrigeration products' unit price has been declining consistently in almost every year over the last 50 years or more.

We applied the learning curve approach using aggregated data for refrigerators, refrigerator-freezers and freezers. First, we estimated an econometric model of historic refrigeration product prices as a function of historic shipments, as shown in equation (1) above. The model produces a very good fit of the data, with an R-squared of 0.98. From this model, we obtain an estimated learning rate parameter b that we use to calculate the learning rate, in accordance with equation (2) above. Our results indicate that the learning rate for refrigeration products combined is about 0.43.

[12] 76 Fed. Reg.9696 (Feb. 22, 2011).

Figure 2. Prices and Shipments of Refrigeration Products Combined



Next, given the estimated values of learning parameter b and the price of the first unit of production P_0, we use historic data on refrigeration products cumulative shipments to obtain estimated prices of the equipment and compare them to the actual historic prices.

Figure 3 below illustrates both actual and estimated inflation-adjusted prices of refrigeration products (in 2009 dollars), which follow each other pretty closely during historic years. This suggests that the learning curve model could be applied to this combination of appliances to project future prices, with a reasonable degree of confidence.

After fitting the model to the historic shipment and price data, we proceed to forecast prices. According to the supplemental data to the NODA,[13] DOE assumes that shipments of refrigeration products will increase linearly throughout 2043 in the base case. We adopt DOE's assumption of linear projected growth of shipments in our analysis.

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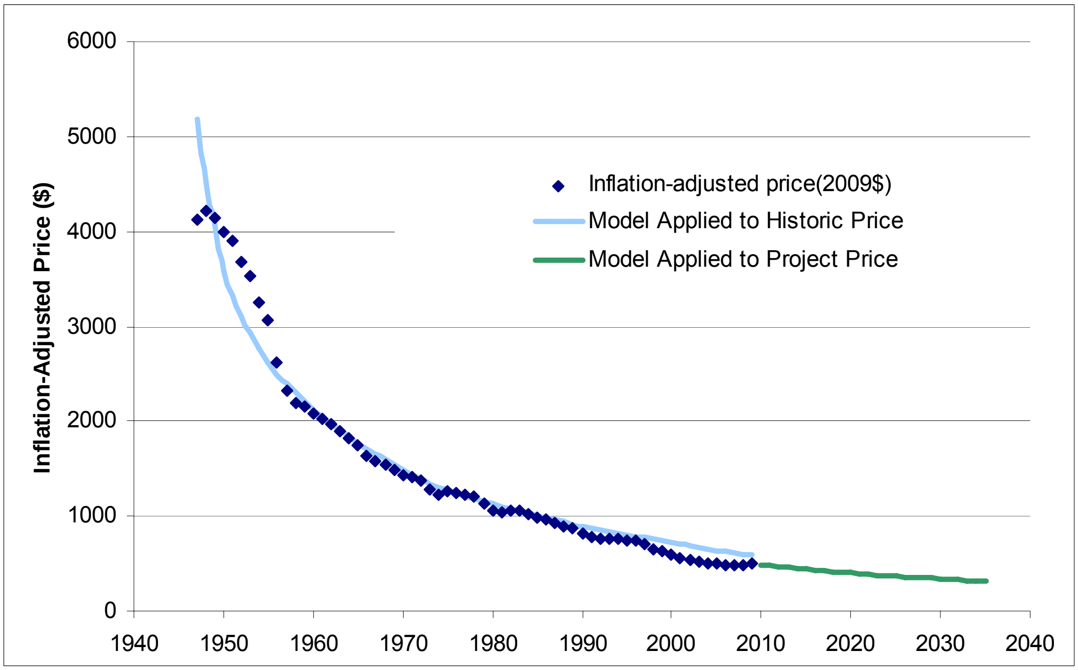
13 Supplemental Information and Data on Equipment Price Forecasting is provided on the DOE website, available at http://www1.eere.energy.gov/buildings/appliance_standards/supplemental_info_equipment_price_forecasting.html

Figure 3. Actual and Estimated Prices of Refrigeration Products Combined



After fitting the model to the historic shipment and price data, we use our calculated learning rate of 0.43 to forecast refrigeration product prices. We use the most recent 2009 average price as a starting point in our projections and then obtain the price trend forecast using the following formula:

> P''=P'·(1-annaul learning rate[14]), where P' is the starting price, and P'' is the projected price for the following year.

Our projected price trend forecast is also illustrated in Figure 3. Refrigeration product average prices continue to decline at a constant learning rate of 43%, while the absolute reduction becomes smaller as price decreases.

One finding that is clear from this analysis is that assuming that refrigeration product prices remain constant in the future will tend to overstate their prices. To demonstrate the potential extent of such an overstatement, we compare a fixed price assumption to forecast prices using the learning curve model, with a learning rate of 0.43. The results through 2030 are presented in Table 3. As shown, the current DOE assumption of fixed real manufacturer costs and retail prices would overestimate refrigeration products' average price by 2030 by $158, or 47 percent.

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14 We calculate annual learning rate = 1 - (annual change in cumulative shipments)$^{-b}$.

Table 3. Refrigeration Products Prices with and without learning curve

Year	Price Without LR (Fixed after 2009), $	Price Projected Using Adjusted LR, $	Price Difference, $	Price Overestimate, %
2010	496	486	10	2%
2015	496	440	56	13%
2020	496	401	95	24%
2025	496	368	128	35%
2030	496	338	158	47%

However, it is possible that some of the products in this combined category behaved differently from the overall trend. Therefore, a better approach would be to investigate how each product behaved independently of the others. We investigate this in the following subsections.

Refrigerators Only

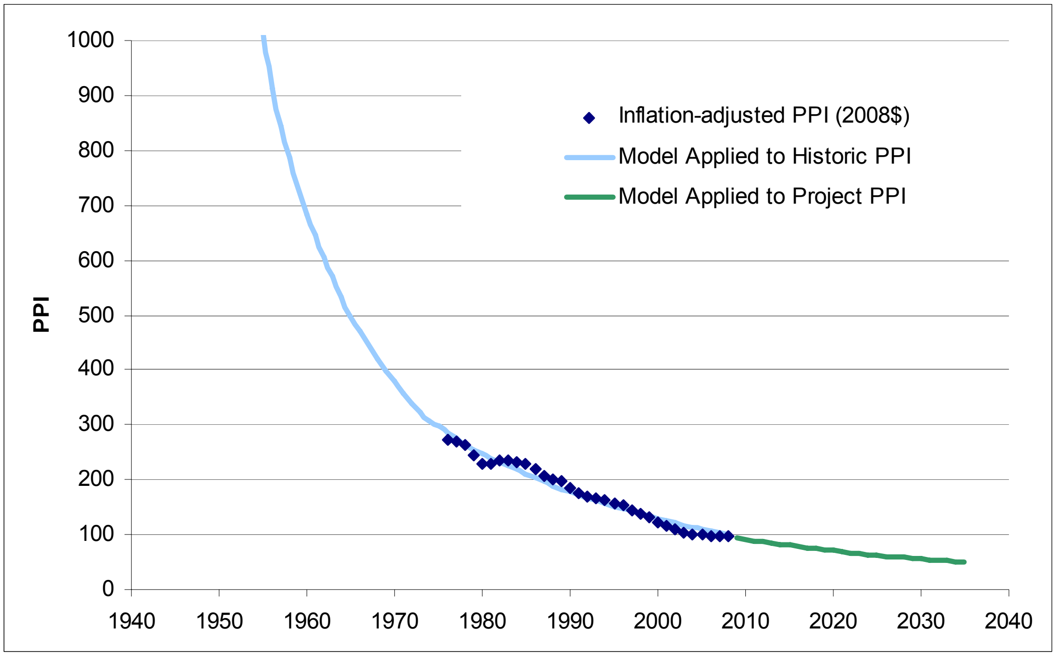
The *Experience Curve* paper estimates learning rates separately for refrigerators and freezers and finds that the learning rate for refrigerators and freezers is 0.52 and 0.38, respectively. In other words, as cumulative production of the corresponding equipment doubles, price declines by 52% for refrigerators and by 38% for freezers.[15]

We apply the learning curve model to similar data sets as described in the *Experience Curve* paper in an effort to replicate this paper's results and to analyze the applicability of the model to the individual equipment data. We were able to find PPI data for refrigerators, used as a proxy for price data, only for the years 1976-2008. With these data, our calculated learning rate for refrigerators is 0.50, which is relatively close to the learning rate in the Experience Curve paper.[16] Applying the learning curve model to the actual shipment data for these historic years indicates that the learning curve model produces a good fit to the actual price data, with an R-squared of about 0.98, as illustrated in Figure 4.

15 DOE, "Using the Experience Curve Approach for Appliance Price Forecasting", February 2011. Supplemental information for the DOE proposal, available at http://www1.eere.energy.gov/buildings/appliance_standards/supplemental_info_equipment_price_forecasting.html

16 We were unable to identify the slight discrepancy between these two results. The discrepancy may be due to differences in the shipment data that were used.

Figure 4. Actual and Estimated Prices (PPI) of Refrigerators Only



After fitting the model to the historic shipment and price data, we use our calculated learning rate of 0.50 to forecast refrigerator prices. We use the most recent 2009 average price as a starting point in our projections and then obtain the price trend forecast using the following formula:

> P''=P'·(1-annaul learning rate), where P' is the starting price, and P'' is the projected price for the following year.

Our projected price trend forecast is also illustrated in Figure 4. Refrigerator average price continues to decline at a constant learning rate of 0.50, while the absolute reduction becomes smaller as price decreases.

Our findings are in line with the Natural Resource Defense Council (NRDC) analysis of refrigerator efficiency and price trends. Figure 5 below presents real prices of refrigerators over time, as well as refrigerator volume and refrigerator efficiency as measured by average energy use.[17] The data in Figure 5 clearly demonstrate the decline in refrigerator prices over time – despite increasing refrigerator volumes and increasing levels of efficiency.

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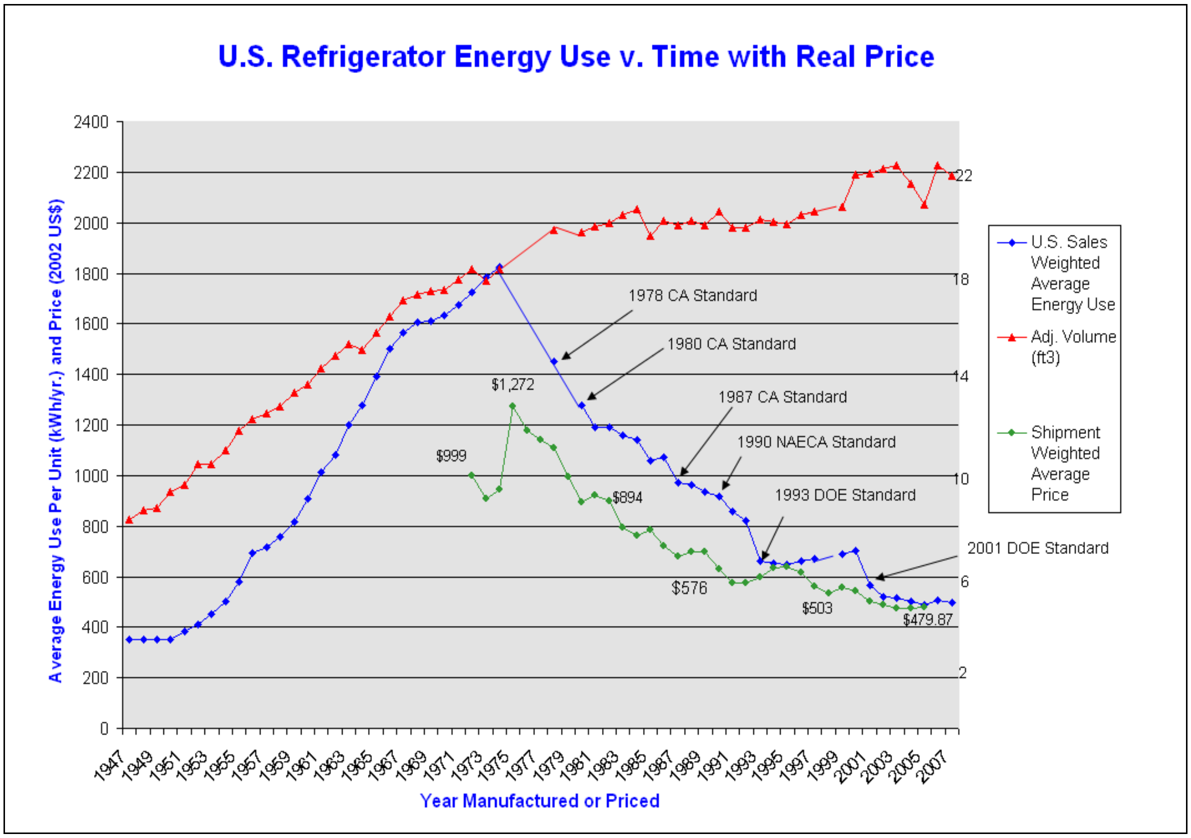
[17] NRDC Stuff Blog, David Goldstein, Some Dilemma: Efficient Appliances Use Less Energy, Produce the Same Level of Service with Less Pollution and Provide Consumers with Greater Savings. What's Not to Like? December 21, 2010. Available at http://switchboard.nrdc.org/blogs/dgoldstein/some_dilemma_efficient_applian_1.html

Figure 5. U.S. Refrigerator Size, Energy Use and Real Price Trends



We again conclude that assuming that refrigerator prices remain constant in the future will likely overstate their prices. When comparing fixed PPI (at 2008 level) to the forecast PPI using the learning curve model, with a learning rate of 0.50, we find that the current DOE approach would overestimate refrigerator PPI by more than 50% in 2025, as shown in Table 4 below.

Table 4 Refrigerator PPIs with and without learning curve

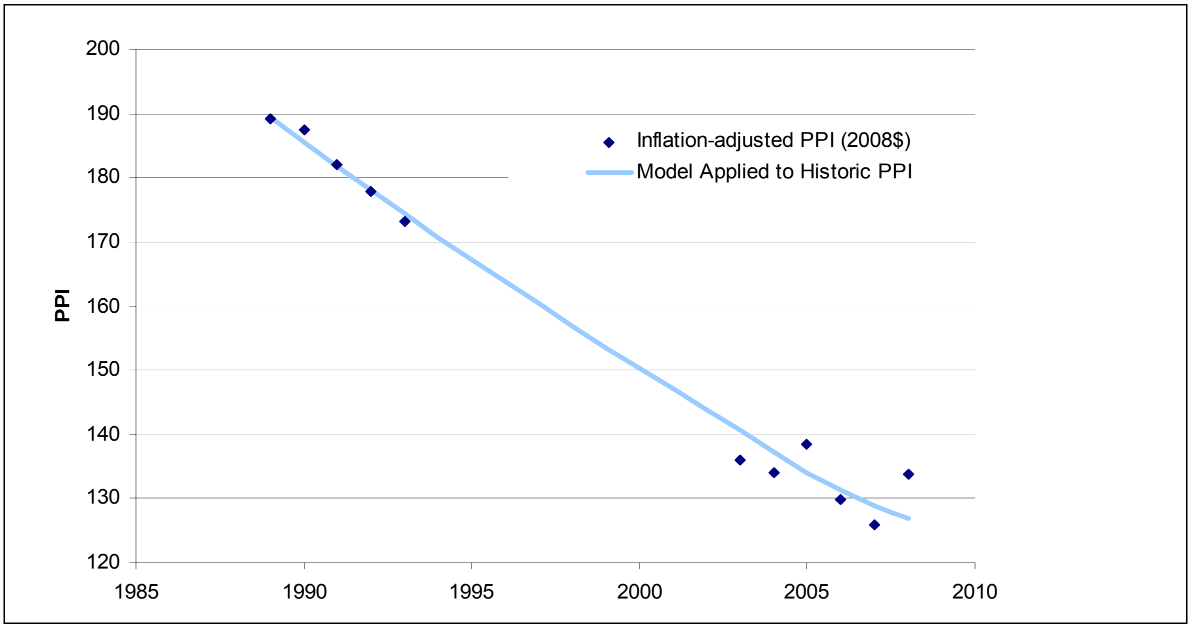
Year	PPI Without LR (Fixed after 2009), $	PPI Projected Using Adjusted LR, $	PPI Difference, $	PPI Overestimate, %
2010	96	92	4	5%
2015	96	80	15	19%
2020	96	71	25	36%
2025	96	63	33	53%
2030	96	56	40	72%

Freezers Only

We were unable to find as much price data for freezers only. In particular, we were only able to find data on PPI for 1989-1993 and 2003-2009. The *Experience Curve* paper, however, reports the same time period of 1989-2009 in their analysis. We applied the learning curve model to these PPI data and shipments data from the DOE supplemental materials. We again estimated an econometric model (1) of historic freezer PPI as a function of historic shipments. Even with only about 10 years of PPI data, the model produces a very good fit of the data, with an R-squared of about 0.98. Using the estimated learning rate parameter b, we obtain a learning rate for freezers of 0.35 which is again close to the learning rate in the Experience Curve paper.

Next, we apply the estimates of the learning rate parameter and the price of the first unit of production P_0 to historic data on freezer shipments to obtain estimated freezer PPI, as defined in equation (1). Figure 6 below illustrates actual and estimated historic PPI for freezers.

Figure 6. Actual and Estimated Prices (PPI) of Freezers Only



At first glance it may appear that the lack of data here creates a problem with regard to whether the learning curve model should be applied to this set of appliances. However, the model applied to the actual historic shipments data produces a good overall fit to the available PPI data. Moreover, based on other applications of experience curves and the combined refrigerator/freezer data, it is safe to conclude that the in-between data points are consistent with the end data points. Even if the actual historic data points between 1994 and 2002 had indicated some fluctuations in prices, the overall price trend would still have indicated a clear decline in freezer prices. With such a clear declining trend, to assume a fixed future price would clearly overstate future prices.

In the NODA, DOE applies the learning curve model to refrigerator and freezer products combined, using CPI data for 1947-1997 and PPI data for 1998-2009. The *Experience Curves* paper applies the learning curve model to refrigerators and freezers separately, using inflation-adjusted PPI data. DOE explains that it has chosen to apply the learning curve model to refrigerators and freezers combined because there is much more CPI data available than PPI data, and the CPI data are available only for combined refrigerator and freezer products.[18]

While it may appear to be appropriate to use the data set with the most information available, we find that this is not the case for refrigerators and freezers. As indicated above, the PPI information for refrigerators for the period 1976-2009 is sufficiently robust to provide a statistically significant learning rate of 0.50. The PPI information for freezers for the period 1989-2009 with a ten-year gap is sufficiently robust to provide a statistically significant learning rate of 0.35. The average price data for refrigerators and freezers combined, provided in the NODA, produces a learning rate of 0.43, which represents a weighted average of the refrigerator and freezer learning rates.

Thus, the additional years of the CPI data do not make the estimated learning rates any more robust, but they do result in less accurate learning rates by combining two products that have different learning rates.[19] In light of this finding, we recommend that DOE apply the learning curve model to refrigerator and freezer products separately, despite the fact that less data are available, because this approach is analytically sound and will result in more accurate forecasts for each product type.

5. Potential Consumer Welfare Impacts

The DOE NODA introduces a discussion of "how consumers trade off upfront costs and energy savings in the absence of government intervention," and seeks comment on whether "analysis of regulations mandating energy efficiency improvements should explore the potential for both welfare gains and losses and move toward fuller economic framework where all relevant changes can be quantified."[20] The NODA also refers to a draft paper that proposes a broad theoretical framework on which an empirical model might be based: "Notes on the Economics of Household Energy Consumption and Technology Choice," Alan Sanstad, Lawrence Berkeley National Laboratory.

While it is not entirely clear what economic framework the DOE is considering, it appears as though it is considering the microeconomic model where economic efficiency is defined as maximizing consumer surplus and producer surplus. If this is, indeed, the framework that the DOE is considering, we would like to raise several concerns about applying this framework to evaluating the costs and benefits of energy conservation standards.

Consumer surplus is defined as the difference between what a consumer would be willing to pay for a good or service and what that consumer actually has to pay. In the context of electricity, it is the difference between a consumer's electricity demand curve and the retail price of electricity. Consumer welfare gains occur when consumer surplus is increased, and consumer welfare losses occur with consumer surplus is decreased.

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18 Based on email correspondence from Lucas Adin, DOE, March 22, 2011.

19 This is not to suggest that it is never appropriate to use learning rates for a combination of product types. Clearly assuming a learning rate of 0.43 for both refrigerators and freezers is better than assuming constant real prices. In this instance, however, we have data available to determine even more accurate learning rates by applying the model to separate products.

20 76 Fed. Reg.9699 (Feb. 22, 2011).

While the consumer surplus model is rooted in widely accepted microeconomic theory, there are several reasons why the model is not well suited for evaluating the costs and benefits of energy conservation standards.

First, as DOE acknowledges in the NODA, consumers tend to undervalue future energy savings for a variety of reasons, e.g., lack of information, lack of sufficient savings to warrant action, inconsistent weighing of future energy bill savings relative to other investments, difficulties in evaluating tradeoffs, and split incentives.[21] These and other factors have been widely recognized as “market barriers” that prevent customers from adopting cost-effective energy efficiency measures. These very market barriers are indications of the limits of the consumer surplus model as applied to electricity services. In order to be representative of any one market, the consumer surplus model relies upon a variety of assumptions, such as: customers have perfect information, there are no barriers to entry for new products, and there are many substitutes for the product. Many of these assumptions do not hold true for electricity services, and therefore the model is of limited value in analyzing the economic efficiency of electricity services. Furthermore, one of the fundamental rationales for government intervention into markets, e.g., in the form of conservation standards, is to overcome market barriers. To apply a model that assumes no market barriers as a way of evaluating such intervention is circular and could produce illogical results.

Second, unlike some products, it is very difficult to identify and quantify a customer demand curve for electricity services (i.e., what they are willing to pay for increasing amounts of electricity). Different customers are likely to have very different price elasticities (consider the different perspectives of low-income, moderate-income and high income customers). Different electric products will also have different elasticities (consider electric life support systems, electric heat in the winter, air conditioning in the summer, versus a television, a video game, or a high-end lighting product.) The price elasticities will also vary by different points in time (consider electric heat in the winter versus electric heat in the summer). Furthermore, some electric products have substitutes, while others do not, making it all the more difficult to determine what a customer would be willing to pay for a certain type or amount of electricity service. While it may be possible in theory to develop a set of demand curves for electricity services, it is unlikely that it would come close to adequately representing all customers, or even all residential customers.

Third, the data, assumptions and methodology underlying the consumer surplus model are complex and therefore limit meaningful participation in the process. The model relies upon economic theory and mathematical modeling that are not readily accessible to typical policy-makers and energy industry stakeholders.[22] This would severely limit the ability of interested parties to fully understand the implications of the analysis or meaningfully contribute to the decision-making process.

Fourth, application of the consumer surplus model would require a variety of data that are difficult to obtain or do not currently exist. The Sanstad paper recognizes this with its statements about the methodology being a useful guide to data development. Our view is

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21 76 Fed. Reg.9699 (Feb. 22, 2011).

22 See, for example, Sanstad, “Notes on the Economics of Household Energy Consumption and Technology Choice.”

that the lack of data makes this method impractical, and the effort that would be involved in developing the data could be better spent elsewhere.

In sum, we believe the DOE's current approach of using life-cycle costing to assess the costs and benefits of energy conservation standards is superior to a consumer surplus model. It is more transparent and accessible to policy-makers, it relies upon data that are more readily available, it does not require the development of customer demand curves, and it is more applicable to electricity services and efficiency products that face a wide array of market barriers.

6. Conclusions and Recommendations

Our review of the data presented in the *Experience Curves* paper and related literature leads to the inescapable conclusion that energy end-use technologies have consistently experienced significant reductions in costs over time. There is no evidence to suggest that such declining cost trends will abate or be reversed in the future, and thus there is no justification for assuming that end-use product costs will remain constant in the future. The observed trends in declining costs are so clear that DOE should not assume future end-use costs will remain constant, unless there is sufficient evidence to support such an assumption.

Ideally, when adequate information is available, DOE should apply the learning curve model to determine a learning rate, and then use the learning rate to forecast future costs. As DOE notes in its NODA, the methodology for determining a learning rate will depend upon the quality of data available for any particular product. In particular, DOE states that:[23]

- *When sufficiently long-term data are available* on the cost trends for a product, an empirical experience curve fit to the available data may be used to forecast future costs of the product.
- When sufficiently long term data are *not* available for forecasting the *cost* of a product, the experience curve cost trend for the product should be applied to the product *price*.
- When sufficiently long term data are *not* available for a *specific product*, it may be appropriate to apply the experience curve cost trend for a *similar product*, or a *product grouping* that includes the product at issue.
- Alternatively, DOE may use *experience curve parameters* from review studies that may indicate that *certain parameter ranges* apply to certain groups of products that include the product under analysis.
- If data are not available for estimating a price trend, DOE may use a *constant real price*, as in past rulemakings.

We agree with DOE's characterization of how the learning curve concept can be applied under different data conditions – with one important exception: we disagree with the option proposed in the final bullet. While it may seem intuitive to assume a constant real price in the absence of better data, the evidence available for so many other products suggests that costs will generally decline over time with increased production. Therefore, assuming some

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[23] 76 Fed. Reg. at 9699 (iemphasis added). .

amount of learning rate – even based on limited data or simplistic assumptions – is likely to be more accurate than assuming costs in the future will remain fixed. We note in Section 2 above that analysts in some industries assume a simple rule-of-thumb learning rate for products where limited data are available. DOE should consider a similar approach for those instances where sufficient data are not available for a particular energy end-use product.

Ideally, DOE should attempt to separately analyze the more efficient models of certain products, as they may have a different learning rate than the standard models. One would expect the newer, more efficient models to have a higher learning rate than the standard models. This approach would provide a better indication of the costs associated with the subset of models that are most likely to comply with future energy conservation standards. However, if it is not possible to do so due to limited data, DOE should use the learning rate for the total product.[24] Such an approach is likely to be a conservative assumption.

We find that in the case of refrigerators and freezers there are sufficient historic data available to apply the learning curve model, and that the resulting learning rate demonstrates a strong statistical fit to the historic data. Furthermore, there are sufficient data available to apply the learning curve model separately to refrigerators and freezers. Therefore, we recommend that the DOE apply the learning curve model to these products, and – in the absence of additional information or analysis indicating otherwise – should use the learning rates presented in the *Experience Curves* paper in forecasting future costs of refrigerators and freezers.

In conclusion, we applaud the DOE's proposal to improve upon the existing methodology for forecasting equipment costs when estimating the impacts of energy conservation standards. The learning curve model offers an analytically sound, widely accepted approach to estimate future cost trends, and there is adequate information available for many energy end-uses to make meaningful forecasts with a sufficient degree of confidence. Continuing to assume fixed product prices will clearly overstate the costs of new efficiency measures, and create an inherent bias against new energy conservation standards.

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24 This is consistent with the option described in the third bullet above.

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