LBNL-6195e

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Accounting for Technological Change in Regulatory Impact Analyses: The Learning Curve Technique

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Energy Analysis and Environmental Impacts Department
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This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technology, State, and Community Programs, of the U.S. Department of Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH1131.

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Executive Summary

Regulatory impact assessment is formally required by the U.S. and many other nations in order to help governments weigh the costs and benefits of proposed regulations, particularly as they compare to those of alternative actions and other government priorities.[1] One of the "best practices" of regulatory impact assessments, as established by the OECD, is to use estimates of costs that are grounded in economic theory. Economic theory indicates that changes in compliance costs should be expected over time as a result of factors related to technological innovation. But many U.S. regulatory impact assessments have traditionally employed a practice that is in conflict with this expectation: they take current estimates of the costs of complying with a proposed regulation and project that those costs will remain unchanged over the full time period that the regulation would be in effect.

There are a number of indications in the literature that ignoring technological change is an important explanatory factor underlying the often-observed tendency for regulatory impact assessments to seriously over-estimate the costs of compliance with new environmental, health, safety, and energy efficiency regulations. The regulatory reform movement has described the appropriate modeling of technological change as an element of "an ideal cost-benefit analysis," and in February 2011, this issue was raised by the U.S. government agency tasked with establishing and enforcing best practices in regulatory impact assessments – the Office of Information and Regulatory Affairs (OIRA) in the Executive Office of Management and Budget. At that time, OIRA called for federal agencies "to use the best available techniques to quantify anticipated present and future benefits and costs as accurately as possible," which include "identifying changing future compliance costs that might result from technological innovation or anticipated behavioral changes."

OIRA, the OECD, and the academic literature do not currently specify the "best available techniques" for accounting for innovation in regulatory impact assessments, however. This report seeks to inform this discussion by focusing on the most widely available technique, which is a learning curve-based cost adjustment method. In vehicle regulation, the Environmental Protection Agency (EPA) and the National Highway Transportation Safety Administration (NHTSA) apply a component-based learning curve approach that the EPA began developing in the 1970s. In energy efficiency regulation for appliances and other products, the Department of Energy (DOE) has applied a whole-product learning curve-based price adjustment approach since 2011. This report: (1) provides an overview of some of the major findings of the academic literature on learning curves in order to inform an assessment of a "best" approach to a learning curve-based regulatory impact assessment cost adjustment technique; (2) describes the EPA-NHTSA and DOE approaches to this technique; and (3) assesses these approaches against the criteria of alignment with economic theory and of administrative sustainability (i.e., fit with existing laws and institutional arrangements, including standard models and relationships between regulators and regulated industries). In the assessment part of the report, we also provide a first-order analysis of the prediction accuracy of the learning curve technique.

[1] The term "regulatory impact assessment" is used in this document in the manner that "regulatory impact analysis" is used in the academic and practitioner literatures on regulatory economics and cost-benefit analysis. We use this wording in order to avoid confusion with the Department of Energy's minimum efficiency performance standards (MEPS) technical support document (TSD) module titled "regulatory impact analysis" or "RIA," which primarily considers non-regulatory alternatives to MEPS.

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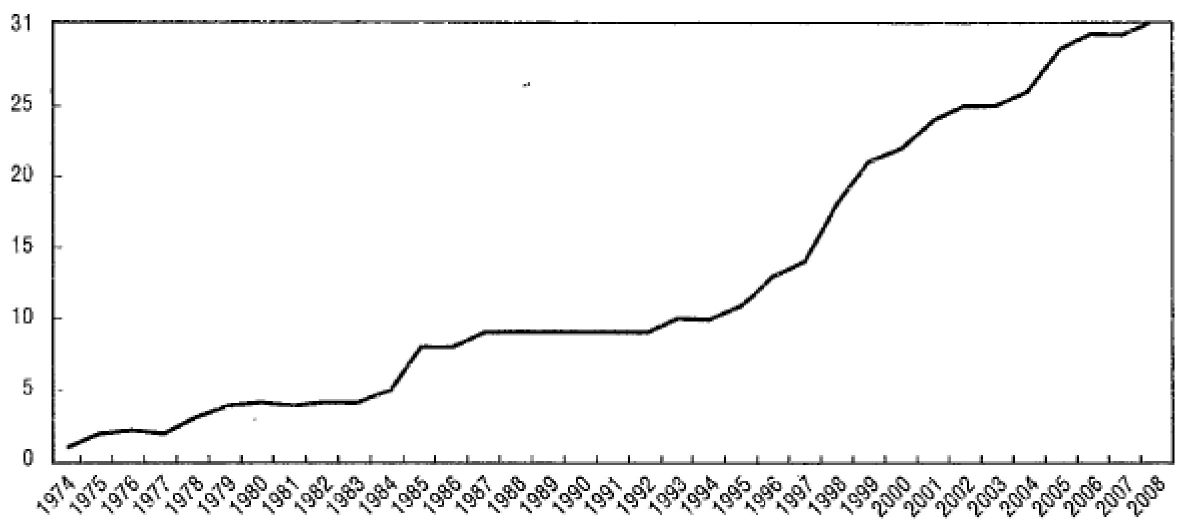
1. Introduction

Regulatory impact assessment plays an important role in U.S. federal energy efficiency regulation, as it does in many other areas of U.S. regulation.[1] Formally required by a growing number of nations (see Figure 1; for more information, see OECD (2009)), regulatory impact assessments are a tool to help governments weigh the costs and benefits of proposed regulatory actions, particularly as they compare against those of alternative actions and other government priorities (e.g., fiscal health, small business support, the operation of free markets, the welfare of various economic and social groups, etc.). Regulatory impact assessments hold great promise for advancing the goals of government transparency and regulatory accountability; to fulfill this promise, the Organization for Economic Cooperation and Development (OECD) has established a number of "best practices" for their conduct. These practices include: the use of transparent and consistent data, assumptions, and models; the assessment of an appropriate range of alternatives to the proposed intervention, including clear and consistent baseline assumptions for the world without the intervention; consideration for discounting the future; sensitivity analysis; attention to non-monetizable/non-quantifiable aspects of a policy and its effects; and estimates of benefits and costs that are grounded in economic theory (Harrington, Heinzerling et al. 2009). In the case of energy efficiency regulation, these best practices help guide the regulatory impact assessment approach employed to analyze, for each proposed minimum efficiency performance standard (MEPS) for a regulated product, the legally required maximum level of energy efficiency that is technically feasible and economically justified, as well as the impacts on consumers and on national energy savings of a proposed MEPS.

Figure 1: Number of OECD jurisdictions with a formal requirement for regulatory impact assessment



Source: (OECD 2009)

The grounding of cost estimates in economic theory is perhaps one of the trickier of the OECD

[1] The term "regulatory impact assessment" is used in this document in the manner that "regulatory impact analysis" is used in the academic and practitioner literatures on regulatory economics and cost-benefit analysis. We use this wording in order to avoid confusion with the Department of Energy's minimum efficiency performance standards (MEPS) technical support document (TSD) module titled "regulatory impact analysis" or "RIA," which primarily considers non-regulatory approaches to MEPS.

best practices for regulatory impact assessments, as economic theory is complex and can change over time. One aspect of economic theory that appears to have been overlooked in designing many U.S. regulatory impact assessment frameworks, for example, is how to think about the compliance cost changes that should be expected over the time a regulation is in effect due to factors related to technological innovation. Traditionally, many U.S. regulatory impact assessment frameworks have taken current estimates of the costs of technologies that comply with a proposed regulation and projected that those costs would remain unchanged over the full regulatory time frame. This would appear to conflict with economic theory, as changes in technology costs can be expected to result from many factors over time, including the successful completion of research and development (R&D) projects, economies of scale, exogenous technological change, direct and indirect labor learning effects, and others. There are a number of indications in the literature that ignoring technological change is an important contributor to the often-observed tendency for *ex ante* regulatory cost projections to seriously over-estimate the costs of compliance with new environmental, health, safety, and energy efficiency regulations (see, e.g., Harrington, Morgenstern et al. 2000; Hwang and Peak 2006; Dale, Antinori et al. 2009; Taylor 2012).[2] These indications – and their implication that associated regulatory decisions unnecessarily forego societal benefit – have helped spur recent influential calls for regulatory impact assessment reform, which describe the appropriate modeling of technological change as an element of "an ideal cost-benefit analysis," although with the expressed caveat that this modeling is "at the frontier of economic research" (Harrington, Heinzerling et al. 2009).

In February 2011, this issue was raised by the U.S. government agency tasked with establishing and enforcing best practices in regulatory impact assessments – the Office of Information and Regulatory Affairs (OIRA) in the Executive Office of Management and Budget – when it provided guidance on presidential Executive Order 13563, the latest in the series of Executive Orders that have institutionalized the principle that the social benefits of new federal regulations should exceed their private costs. At that time, OIRA called for federal agencies "to use the best available techniques to quantify anticipated present and future benefits and costs as accurately as possible," which include techniques that identify "changing future compliance costs that might result from technological innovation or anticipated behavioral changes" (OMB 2011). But OIRA, the OECD, and the academic literature do not currently provide detailed guidance on these "best available techniques" for accounting for innovation in regulatory impact assessment.

This report seeks to inform this discussion by focusing on the most widely available technique – learning curve-based adjustments to projected costs – which the Environmental Protection Agency (EPA), the National Highway Transportation Safety Administration (NHTSA), and the Department of Energy (DOE) have all incorporated variations of in numerous regulatory impact assessments. The key difference between the approaches used by these agencies is their focus on the manufacturing cost of the components that enable compliance with a regulation, as opposed to the commercial price of the whole product that has to meet the new standard. The EPA and NHTSA take a component-based learning curve approach, which the EPA began developing in

[2] Harrington, Heinzerling et al. (2000) is the most comprehensive of these studies. The paper reviews *ex ante* analyses of 28 regulations across a variety of fields, finding that approximately half overestimate unit cost and total cost by more than 25%. Note that both exogenous and induced technological change (the latter due to increased investments directed toward compliance) are frequently cited in the literature as relevant to regulatory cost overestimates. Other explanations include lack of commitment by firms (in providing accurate cost estimates for possible future regulation) as well as errors by regulators who have asymmetric information regarding firm resources and dynamic capabilities.

the 1970s (referred to here as the "EPA-NHTSA approach"), while the DOE takes a whole product-based learning curve approach (referred to here as the "DOE approach"), which it initiated in 2011.

In assessing the learning curve technique for accounting for innovation in regulatory impact assessments, we focus on two criteria. First, the technique must be grounded in economic theory, in keeping with OECD best practices. Second, it must be administratively sustainable (i.e., it must fit with existing legal and institutional precedent, including standard models and relationships between regulators and regulated industries).

This report is divided into four major sections, as follows. After this introductory section, the second section focuses on defining the economic theory that a learning curve technique for adjusting regulatory cost estimates should align with by providing an overview of some of the major findings of the academic literature on learning curves. In the third section, we describe the learning curve technique as it has been used to date in the EPA-NHTSA approach and in the DOE approach. In the fourth section, we provide a first-order analysis of the prediction accuracy of the learning curve technique, as well as recommendations for the ongoing development of learning curve-based techniques for adjusting the cost estimates in regulatory impact assessments.

2. Background on "Learning Curves"

The focus of this section is on understanding the economic theory underlying the learning curve phenomenon that agencies are interested in marshalling in order to adjust the cost estimates in their regulatory impact assessments. It should be stated up-front, however, that several disciplines have contributed to the crafting of the current economic understanding of learning curves. Learning curves originally emerged from individual learning and psychology studies in which it was repeatedly demonstrated that the more times a task is performed by an individual, the less time is required for the individual to perform each subsequent iteration of that task. The concept was later extended to organizations and industries in studies focused on productivity in manufacturing, such as the production of Liberty Ships and aircraft (see, e.g., Wright 1936; Alchian 1963; Rapping 1965). In these and later management studies, economists, psychologists, and sociologists in the field of organizational behavior united behind the empirical observation that as more units of a good are produced, the less it costs to manufacture each subsequent unit. Note that the initial focus of the voluminous management literature on learning curves was on documenting their existence, magnitude, and shape in many different empirical settings. Over the past two decades, however, the management literature has focused primarily on explaining the factors that underlie the learning curve, in an effort to make the phenomenon of more practical use to managers. Meanwhile, the energy policy literature adopted the learning curve concept at least as far back as the early 1990s, initially in order to assist in modeling technological change endogenously in long-term integrated assessment models of global climate change. Beyond this application, the energy policy literature has also worked to empirically describe learning curves in energy supply and demand technologies, with a particular focus on their implications for the costs of emerging renewable energy technologies. Note that as the energy policy literature on learning curves tends to focus on determining functional form for use in modeling, rather than on the economic factors underlying the learning curve phenomenon, this literature is not a primary focus of this review.[3]

2.1 Learning Curves in the Academic Literature

At its heart, a "learning curve" is a mathematical representation of the concept that with continuous production, production knowledge and experience grow and result in economies. The most commonly used and most robust functional form of an organizational learning curve is the power function presented in Equation 1 (see Kantor and Zangwill 1991). The dependent variable here is unit costs, while the independent variable here, as it is in most learning curve formulations, is the cumulative number of units produced, which is a proxy for knowledge acquired through production until the current period (this is sometimes expressed as lagged cumulative output, since the current period's output does not go into the accumulated knowledge stock). Note that it is important to have a sense of how to bound the count of units (i.e., understand which unit is the first unit, both temporally and spatially). In interpreting this equation, it is understood that if unit costs decrease as a function of the cumulative number of units produced, *ceteris paribus*, organizational learning is said to occur (Argote and Epple 1990).

Equation 1: The traditional functional form of an organizational learning curve

$$C(X_t) \; = \; C_0 * X_t^{-b}$$

where:

$C(X_t)$ = the cost of the cumulative production accrued through period *t-1*
C_0 = the cost of the first item made
X_t = the cumulative number of units produced through period *t-1*
b = a parameter that measures the rate costs are reduced as cumulative output increases

It is simpler for estimation purposes if the power function in Equation 1 is expressed on a logarithmic scale so that the data more closely resemble a straight line. The general form of that logarithmic equation is expressed in Equation 2, although additional predictor variables – already in log form – are usually included in this equation (see Levin 2000). If the coefficient of the cumulative output variable in Equation 2 is statistically significant when the equation is estimated with appropriate control variables, learning is said to occur (see Argote 1999).

Equation 2: The estimation form of the traditional organizational learning curve

$$ln\, C_t \; = ln\, C_0 - b\; ln\, X_t$$

The effects of the learning curve are generally discussed using the language of Equations 3 and 4. Equation 3 defines the progress ratio (PR) as the percentage of the initial unit cost that is left after cumulative output doubles, while Equation 4 defines the learning rate (LR) as the percentage reduction in unit cost that is associated with each doubling of cumulative output. For example, a progress ratio of 80% means that each doubling of cumulative output leads to a 20% reduction in unit cost, which would be known as the learning rate (with the value for b in Equation 1 of 0.322).

[3] The energy policy literature may be starting to reinvent concepts and methods found in the management literature, however (see, e.g., the use of "two-factor" and "multi-factor" learning curves as ways to model, if not empirically understand, the factors underlying the learning curve in articles like Mayer, Kreyenberg et al. (2012)).

Equation 3: The progress ratio

$$PR = 2^{-b}$$

Equation 4: The learning rate

$$LR = 1 - 2^{-b}$$

Figure 1 and Figure 2 present the basic economic intuition behind learning curves. In Figure 1, we assume a market with downward-sloping demand in any given time period (D_t). Additionally, we make the simplifying assumption of a perfectly elastic supply curve in any given time period (S_t). The market equilibrium price – used to proxy cost – and quantity (P_t and Q_t respectively) are determined in each period such that the market clears. Figure 2 takes this market and conceives of the learning curve graphically as a shifting down of the supply curve as producers gain more production experience. This is depicted in the left-hand panel of Figure 2: there is some rate by which the supply curve shifts down as a function of past production (summarized by the variable X_t, which is the sum of all production in units of Q prior to date t, using the index variable of little s to represent that period of time). Learning can therefore be conceptualized as the degree to which it becomes cheaper to produce the same level of quantity as a function of past production experience. Continuing with the simplifying assumption of a perfectly elastic supply curve, the incremental downward progression of the market equilibrium price over time (i.e. over an accumulation of more past production) can be assumed to be due to this learning. The rate by which prices drop as a function of an increase in past production is estimated as (–b), which is a measure of the learning effect in the market. The way this estimation relates to the market can be seen in the right-hand panel of Figure 2.

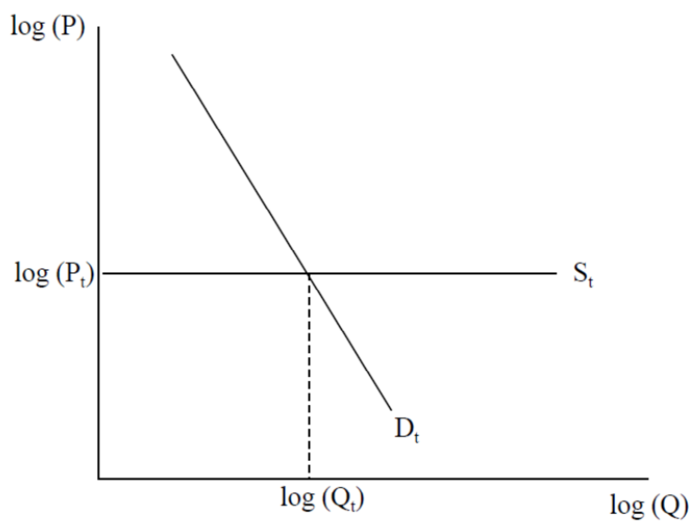


Figure 2: A market with downward-sloping demand in any given time period (Dt) and a perfectly elastic supply curve in any given time period (St).

Note: The market equilibrium price and quantity (Pt and Qt respectively) are determined in each period such that the market clears.

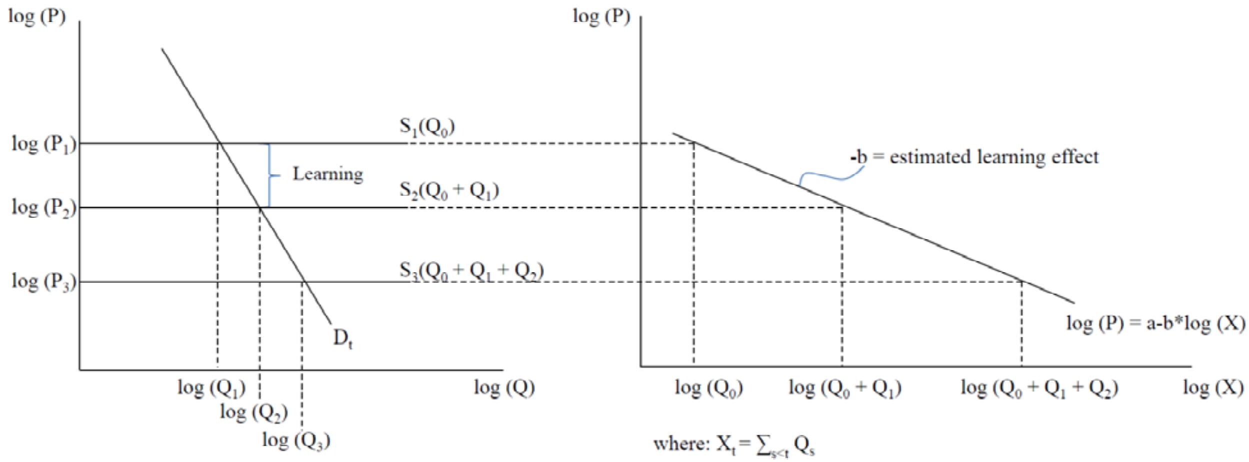


Figure 3: A market in which the supply curve shifts down as producers gain more production experience.

Note: The variable X_t, is the sum of all production in units of Q prior to date t, while the learning effect (-b) is conceptualized as the degree to which the market equilibrium price (P_t) to produce the same level of quantity declines as a function of past production experience.

Improvement correlated with production experience by organizations has been documented in myriad empirical studies over the past 75-plus years, with improvement typically measured by the unit cost of production, but sometimes by other performance or quality indicators, such as reduction in complaints or industrial accidents. Variables are not interchangeable in derivations of "learning curves," however. For example, calendar time is not as good a predictor of an organization's improvement with experience as is its own cumulative output (Rapping 1965; Lieberman 1987; Argote and Epple 1990). Similarly, using price as an outcome metric – although frequently done in the literature – can be misleading. Whereas cost changes occur over time due to such things as changes in input prices and production efficiency, price changes can occur from several other factors, including joint determination with output, which can lead to learning curves that are statistically unidentified, without enough observations. To be most useful in learning curve estimation, price-cost margins need to be constant over time. This, unfortunately, requires a number of unlikely things to stay constant in an industry, such as the number of producers, the elasticity of demand, and the return on equity for producers. For a useful discussion, see Papineau (2006).

Organizations vary considerably in their rates of improvement (see, e.g., Yelle 1979; Hayes and Clark 1986), as documented most famously in Dutton and Thomas (1984), which reviewed the progress ratios (i.e., the percentage of the initial unit cost found with each doubling of cumulative output) observed in 22 field studies of 108 manufactured items in a wide range of industries. In the frequency distribution of progress ratios illustrated by Dutton and Thomas (1984) and displayed in Figure 4, the average progress ratio is 81-82% (i.e., an 18-19% unit cost reduction per doubling of cumulative output), the maximum progress ratio is 55% (i.e., a 45% improvement per doubling), the minimum positive progress ratio is 95% (i.e., a 5% improvement per doubling), and in one instance, a negative progress ratio of 107% is observed (i.e., a 7% unit cost *increase* per doubling). Similar results have been found in recent reviews of the Dutton and Thomas (1984) data as well as many energy supply and demand learning curve studies, which reveal within-technology variation in progress ratios often as large as between-technology variation, but approximately normally distributed around a mean of 82 ± 9% (i.e., an 18% improvement per doubling; see: Ferioli, Schoots et al. 2009; Weiss, Junginger et al. 2010).

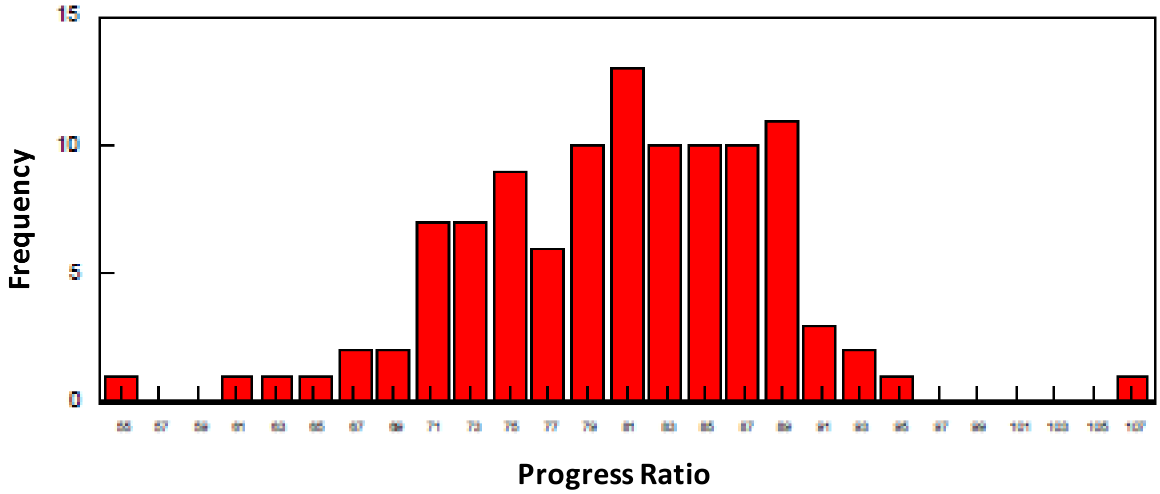


Figure 4: Distribution of progress ratios documented in the studies reviewed in Dutton and Thomas (1984).
Source: Dutton and Thomas (1984)

The original learning curve concept – as production continues, production knowledge and experience grow and result in economies – was influenced by experimental psychology research which typically finds that the more times an individual performs a task, the better that individual is able to perform each subsequent task (Argote and Epple 1990). In the organizational setting, however, individual learning by workers performing tasks (i.e., direct and indirect labor learning in the context of a given set of capital goods) is often only one of several factors that help to explain progress ratios. For example, labor learning was only one of the four main categories of factors Dutton and Thomas (1984) identified as explaining, either singly or in combination, the progress ratios in the studies they reviewed. The others were: (1) effects of technological change in the production environment due to capital investment, which contribute to an organization's knowledge and experience (see, e.g., Arrow 1962; Sheshinski 1967; Joskow and Rozanski 1979); (2) local industry and firm characteristics, particularly with regard to the degree of mechanization, the distinction between assembly and machining, the length of cycle times, and the type of manufacturing process (see, e.g., Hirsch 1952; Hirsch 1956; Adler and Clark 1991); and (3) effects which result from changing production techniques in order to absorb indivisible costs and exploit other economies that emerge as an organization anticipates increased production (note that because of the aggregate nature of the "learning curve," there have long been instances of cost reductions due to scale economies being misattributed as the effects of organizational knowledge or experience – see, e.g., Conway & Schultz (1959), Wright (1936) – which is why Dutton and Thomas (1984) includes scale effects as a factor in explaining progress ratios).

Beyond those factors discussed in Dutton and Thomas (1984), factors that explain variation in progress ratios include: organizational forgetting (i.e., knowledge depreciation; Argote and Epple (1990)); employee turnover (ibid.); transfer of knowledge across products, business lines, and organizations (ibid.);[4] level of interdependence between organizational units (e.g., through vertical integration, see Sorenson 2003); management practices such as debriefing activities, coaching behavior, use of formal procedures, and use of cross-functional communication (Pisano, Bohmer et al. 2001); and volatility in the competitive environment (Sorenson 2003).

To simplify this list of factors, Dutton and Thomas (1984) laid the foundations for a long-standing approach to distinguishing between factors that can be "induced" by management versus developed "autonomously" by labor, with both sets influenced by endogenous as well as exogenous sources of innovation (see, e.g., von Hippel 1976). Induced learning (also known as second-order learning – see Adler and Clark (1991)) stems from the formal knowledge generation and transfer practices of management (e.g., R&D investments; employee training programs; organizational practices, procedures, and rules; etc.), while autonomous learning – which is most commonly referred to by the labels of learning-by-doing, learning-by-experience, first-order learning, etc. – stems from informal experiments and process refinements by employees in order to execute tasks more cost-efficiently (see Adler and Clark 1991; Wiersma 2007). Autonomous learning often occurs in stable organizational contexts in which the opportunity to develop experience is present, while induced learning tends to occur when firms redefine their strategy, often in response to competitive opportunities and threats (Fiol and Lyles 1985). Argote et al. (2003), meanwhile, suggests that the list of explanatory factors can be simplified by focusing on the degree to which employees and/or organizations have the ability, the opportunity, and the motivation to learn in a given context.

Note that most, but not all, of the academic literature on learning curves since the early 1990s focuses on explaining observed variation in firms that adopt a new technology, start producing new products, or open new plants or production lines (for a discussion, see Wiersma (2007); useful references include Adler and Clark (1991), Argote et al. (1990), Pisano et al. (2001), Sorenson (2003), and Reagans (2005)). Firms that provide established products and/or use more mature technologies can still maintain positive learning curves, however, as well as experience occasional sudden reductions in average cost if, for example, a new technology is implemented (Wiersma 2007).

2.2 Considerations for the Predictive Use of Learning Curves

Managers and policy-makers have long been interested in marshalling the learning curve as a practical tool, rather than simply a descriptive one. The learning curve has been used in a variety of management settings, informing organizations in their efforts to: formulate manufacturing strategy, develop production schedules, establish pricing and marketing approaches, direct employee training, predict the costs confronting competitors, and decide on the utility of and approach to subcontracting production Argote and Epple (1990).[5]

The implied framework for application is to use past experience to predict future progress ratios that can be used for various purposes, including estimating the improvement possible with the manipulation of cumulative output. But in order to predict progress ratios accurately based on the past requires the progress ratio to be reliable – i.e. subject to the same variation over time and space – and consistently explainable (Dutton and Thomas 1984). Given the very long list of

[4] There is often more variation across organizations or organizational units producing the same product than within organizations producing different products; see Argote and Epple (1990).

[5] In addition, before they were used to inform regulatory impact assessments in a formalized way, learning curves were used to inform other policy areas, such as antitrust and international trade policy (Argote and Epple 1990).

explanatory factors underlying learning curves, it is perhaps not surprising that large errors have been observed when attempting to project future progress ratios based either on an industry's historic progress ratio (derived from industry-wide learning curves, which are typically called "experience curves") or on a firm's own progress ratio. In a very helpful discussion of this topic in Dutton and Thomas (1984), the authors point out that Alchian (1963) found mean prediction errors in both cases of 22-25%, and other studies echoed this unreliability (see, e.g., Hirsch 1952; Hirsch 1956; Conway and Schultz 1959; Billon 1966). Indeed, firms that have used the "learning curve" concept for planning purposes have been found to achieve smaller-than-expected profits (see, e.g., Porter 1980; Kieschel 1981).

Thus, although the "learning curve" effect is widely observed, it cannot be used for prediction without caution. Given the standard deviation of about 9%-points around the average progress ratio, Weiss (2010) warns that projecting beyond three or four doublings of cumulative production results in substantial under- or over-estimation of production costs. Accuracy of estimation is also influenced by the way that doubling of cumulative production is calculated (i.e., by organizational unit, organization, industry, nation, or region; see Nemet 2009). Note that there is recurring but currently unpredictable evidence of knowledge depreciation as it flows across such units of analysis (Argote 1999). There is also evidence that the degree of maturity of a product or a production technique makes a difference to the shape of the learning curve. When a technology is new, there are significant degrees of freedom in redesigning processes to make them more efficient; the learning curve at this stage is often steep (Wiersma 2007). When a technology is mature and its production is fixed, however, autonomous learning tends to dominate induced learning, and at this stage, the curve generally starts to level out such that additional cumulative output has less and less impact on the improvement metric (see Adler and Clark 1991; Wiersma 2007). Older studies within single manufacturing facilities have found learning curves to become essentially flat after approximately two years (Baloff 1966; Hall and Howell 1985).

3. Use of Learning Curves in Regulatory Impact Assessments

The Environmental Protection Agency (EPA), the Department of Transportation's National Highway Transportation Safety Administration (NHTSA), and the Department of Energy (DOE) have all incorporated learning curves into their regulatory impact assessments for various policies. The EPA pioneered the technique for all U.S. regulatory impact assessments in its cost estimation of vehicle emissions standards for traditional air pollutants (e.g., nitrogen oxides, carbon monoxide, particulates, etc.), dating at least as far back as 1978 (see Lindgren 1978). The approach was formalized by EPA throughout the 1990s, and was then generally followed – with some modifications – by NHTSA as it developed regulatory impact assessments for Corporate Average Fuel Economy (CAFE) standards in the late 2000s that were designed to partner with EPA efforts to regulate vehicle greenhouse gas emissions. We use the term "the EPA-NHTSA approach" in order to highlight the similarities in the techniques used by these two agencies. The DOE application of learning curves to its regulatory impact assessments for appliance MEPS began in 2011 under the Obama administration, many years after the EPA-NHTSA approach was developed. This "DOE approach" differs in other significant ways from the EPA-NHTSA approach. This section delves into some of the details of these contrasting approaches, providing for each: (1) the general regulatory impact assessment framework of the agency; (2) a chronology of recent regulatory impact assessments that incorporate the agency's learning curve-based cost adjustment approach; and (3) a description of the general framing, derivation, and application of the agency's approach.

3.1 Use of Learning Curves in Vehicle Regulations

This section summarizes the EPA-NHTSA approach to incorporating learning curve-based cost adjustments in regulatory impact assessments. This approach has been practiced for more than 15 years in the area of vehicle emissions regulation (clearly documented since at least 1997, although the practice dates back at least to 1978) and fuel economy regulation (clearly documented since 2008). The EPA-NHTSA approach is essentially a component-based learning curve approach (for more information, see Kantor and Zangwill 1991; Ferioli, Schoots et al. 2009), in that it focuses on using a learning rate to appropriately adjust the cost of the various components that enable compliance with a new regulation, rather than adjust the cost of the full product as a technological system that is more-or-less a "black box."

a. General EPA-NHTSA Regulatory Impact Assessment Approach

EPA's traditional regulatory impact assessment approach coordinates well with a component-based learning curve cost adjustment technique.[6] In its framework, the EPA defines a set of features that can alter a vehicle's emissions (or fuel economy, in the case of NHTSA) in order to meet the proposed standard (i.e., a "technology package"). Cost projections are estimated for each component in the technology package based on product tear down studies, such as those used by manufacturers to benchmark their products against competitors, as well as from confidential data either submitted by vehicle manufacturers or obtained through individual meetings with major original equipment manufacturers (OEMs) that account for most (~90%) of the vehicles produced for sale in the U.S. Besides estimating piece costs for all candidate technologies, the EPA estimates direct manufacturing costs and cost markups to account for manufacturers' indirect costs, considering known manufacturer practices, such as making major changes to model technology packages during a planned redesign cycle. Note that EPA models a baseline U.S. fleet of vehicles using estimates of current production volume based on EPA's vehicle emissions certification data, data purchased from Ward's Automotive Group, and CAFE certification data (U.S. Environmental Protection Agency and U.S. Department of Transportation 2011).

The cost difference between technology packages depends on the types of components included, the maturity of those components, the cost of their materials, and the cost of associated labor. Costs are categorized as either direct or indirect, long- or short-term. Table 1 provides a few examples of the types of components that can be included in a technology package and their estimated costs.

[6] Unless otherwise specified, the regulatory impact assessment framework described here for EPA applies to NHTSA as well.

Table 1: Example component costs ($ per vehicle)

Technology	Relevant System	Small Car	Large Car
Cylinder deactivation	Base engine	--	$203
Camless valvetrain (electromagnetic)	Base engine	$336-673	$336-673
Diesel – Lean NOx trap	Base gasoline engine	$2790	--
Optimized E20-E30	Base gasoline engine	$713	$143

Source: EPA (2008)

b. Chronology of the Use of Learning Curves in Vehicle Policy Regulatory Impact Assessments

As depicted in Table 2, learning curve-based cost adjustments have been formally incorporated into vehicle regulatory impact assessments for many years; the practice can clearly be documented as far back as the EPA's 1997 Emission Standards for Heavy-duty Diesel Engines Used in Trucks and Buses, although it can be traced through references as far back as 1978 (see, e.g., Lindgren 1978; E.H. Pechan & Associates 1994; U.S. Environmental Protection Agency 1997).

Table 2: Vehicle policy regulatory impact assessments incorporating learning curve cost adjustments

Date	Agency	Policy
1997	EPA	Heavy-Duty Highway Emissions Standards
1998	EPA	Non-Road Diesel Vehicles Emissions Tier 2/Tier 3
1999	EPA	Motor Vehicle Emissions Standards and Gasoline Sulfur Control Requirements: Proposed Rule for Tier 2
2000	EPA	Control of Air Pollution from New Vehicles: Tier 2 Motor Vehicle Emissions Standards and Gasoline Sulfur Control Requirements
2000	EPA	Heavy-Duty Engine and Vehicle Standards and Highway Diesel Fuel Sulfur Control Requirements
2004	EPA	Control of Emissions from Non-road Diesel Engines: Tier 4
2008	EPA	Control of Emissions of Air Pollution from Locomotives and Marine Compression-Ignition Engines Less Than 30 Liters per Cylinder
2008	NHTSA	Average Fuel Economy Standards Passenger Cars and Light Trucks, Model Year 2011
2010	EPA, NHTSA	Light Duty Vehicle Greenhouse Gas Standards and Corporate Average Fuel Economy Standards
2011	EPA, NHTSA	Greenhouse Gas Emissions Standards and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles
2012	EPA, NHTSA	Light Duty Vehicle Greenhouse Gas Standards and Corporate Average Fuel Economy Standards

Source: EPA and NHTSA Regulatory Impact Assessments in (1997; 1998; 1999; 2000a; 2000b; 2004; 2008; 2008b; 2010; 2012)

c. EPA-NHTSA Framing of the Learning Curve Approach

In each regulatory impact assessment, the EPA frames its use of learning curves with an explicit call-out to the academic literature, and in particular, the aforementioned Dutton and Thomas (1984) and Argote and Epple (1990). The agency provides the distribution of progress ratios presented in Dutton and Thomas (1984) and reproduced in Figure 4, as well as cites other studies, such as Alchian (1963) and Benkard (2000), in support of the point that although there is a considerable amount of variation in the empirical observation of progress ratios, it is justified for the agency to select a progress ratio from other industries when trying to assess the costs of the components of a given technology package which are necessary to achieve compliance. The EPA acknowledges that learning curve effects can be lower in some industries (e.g., chemicals, nuclear power with approximately 11% savings; see Zimmerman 1982; Lieberman 1984), and difficult to decipher in others (e.g., the computer chip industry; see Gruber 1992).

The EPA also notes that areas involving direct labor and material cost savings are usually the source of the greatest savings; cited examples include a reduction in the number or complexity of component parts, improved component production, improved assembly speed and processes, reduced error rates, and improved manufacturing processes. These sorts of improvements all result in higher overall production, less scrappage of materials and products, and better overall quality. The agency is careful to provide statements related to these topics in its regulatory language because they help ground agency decisions on when it is appropriate and inappropriate to apply learning curves to compliance cost estimates.

d. EPA-NHTSA Derivation and Application of Learning Curves to Adjust Cost Projections

The standard method and terminology used in the EPA-NHTSA approach today is described in detail in a 2008 staff technical report on the light-duty vehicle rulemakings for emissions of carbon dioxide and greenhouse gases, as well as for fuel economy (U.S. Environmental Protection Agency 2008; U.S. Environmental Protection Agency and U.S. Department of Transportation 2011).

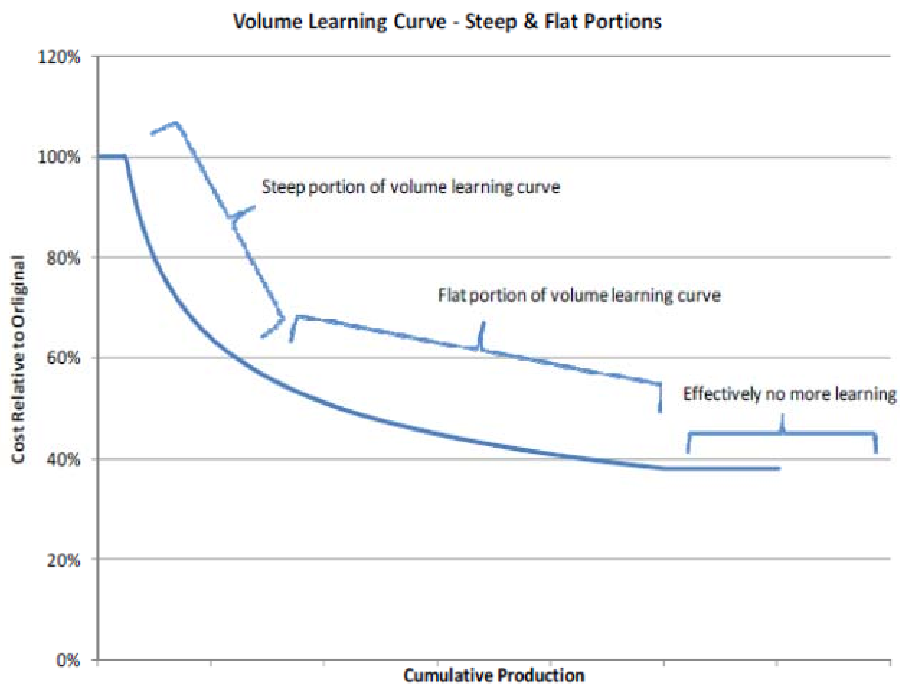
The basic EPA-NHTSA approach has two parts. First, it selects a learning rate that is informed by a review of the literature (officially Dutton and Thomas 1984, although the fact that the EPA-NHTSA approach tends to use a learning rate of 20%, rather than 18-19%, implies a lingering influence of earlier government uses of learning rates in areas like antitrust policy and budgeting). Second, it applies that rate to the long-term direct costs (e.g., materials and labor) of the technology package that can alter a vehicle’s emissions/fuel economy, as well as applies it to related consumer costs (i.e., vehicle purchase price rather than vehicle operating cost). The EPA-NHTSA approach explicitly does not apply the learning rate to the indirect costs (e.g., R&D, corporate operations, marketing, etc.; see EPA (2011)) of the technology package. In addition, the approach exercises some discretion as to whether or not to apply the learning curve adjustment to all components of a technology package, a situation which we describe in more detail below.

1. Derivation of Learning Curves

For many years – until NHTSA joined the EPA in applying learning curves in regulatory impact assessments – the EPA-NHTSA approach cited the literature as justifying the selection of a progress ratio that would result in a learning rate of 20% (i.e., a 20% reduction in cost for each doubling of production volume) for its technology package cost adjustment, unless it decided that no learning was likely to occur.

Once NHTSA joined the EPA in applying a learning curve-based cost adjustment approach, however, the EPA-NHTSA approach stopped using only a single 20% learning rate and instead selected a few learning rates that it deemed to be appropriate to more and less mature and widely adopted technologies. Figure 5 shows the distinction the EPA-NHTSA approach begins to make in the late 2000's between newer versus more mature technologies, in keeping with a major thread in the management literature on learning curves and the distinction found in that literature between phases in a technology's development in which induced and autonomous learning are more likely to play a role (see, e.g. Wiersma 2007). For newer technologies, the EPA-NHTSA approach explains that there is likely to be substantial learning in the near future – i.e., through induced learning – and it selects a "steep" learning rate of 20% for use in adjusting the relevant component costs. For more mature technologies that the agency judges to be widely available commercially, the EPA-NHTSA approach selects a "flat" learning rate (1-3%) or no learning rate (0%), in order to reflect the more limited learning opportunities associated with autonomous learning.

Figure 5: Tailoring the learning rate in the EPA-NHTSA approach



Source: (U.S. Environmental Protection Agency and U.S. Department of Transportation 2011)

2. Application of Learning Curves

In applying the learning rate to adjust the direct costs of components of technology packages, the EPA-NHTSA approach has to make determinations about the maturity and diffusion of those components. It is aided in this by the agencies' access to product tear-down studies and confidential data from OEMs, derived either from submissions or meetings, as well as the agencies' access to vehicle emissions and CAFE certification data and data from Ward's Automotive Group. These data arrangements give the EPA and NHTSA an important understanding of industry practices, such as product redesign cycles, as well as access to relevant expertise that can inform determinations of new versus mature technologies.

When applying the learning rate to the direct costs of technology package components, the EPA-NHTSA approach makes the simplifying assumption that the production volume of the technology package is tied to the product cycle times of the automobile industry (shown to have been reduced from five years to four years by the end of the 1990s). For example, in many regulatory impact assessments, the EPA-NHTSA approach assumes that a certain number of years after the imposition of a standard, the production volume of the technology package will double, and after another like period of time, production will double a second time.[7] In years after this second doubling of production, the agencies assume that the technology package will become mature and the potential for further learning will be diminished as autonomous learning sets in. As a result, in many regulatory impact assessments the EPA-NHTSA approach only applies the learning rate to the first two time periods (i.e. as production doubles the first two times) and does not adjust costs with a learning rate after this time.

As mentioned above, the EPA-NHTSA approach does not automatically adjust the direct costs of *every* component of a technology package by use of a learning rate; this was true even during the era of a uniform 20% learning rate or no learning rate, which was prevalent before NHTSA joined with EPA in applying learning curves to regulatory cost estimates. For example, in EPA's Tier 2/Tier 3 Non-Road Diesel Vehicles Emissions regulatory impact assessment in 1998, EPA chose not to apply a learning rate adjustment for such technology package components as: catalysts (due to the uncertainty of future precious metal prices), evaporative system costs (on the principle that these had already been well developed and anticipated system improvements were likely to be employed easily by manufacturers), and software costs (since they were deemed unlikely to align with manufacturing progress ratios). Note how these rationales for applying or not applying the learning rate reveal the agency's degree of familiarity with the state of the industries involved in manufacturing the relevant components.

Table 3 presents an example of the discretion employed by the EPA-NHTSA approach in applying different learning rates to different components of a technology package as part of the 2012 regulatory impact assessment for emissions of carbon dioxide and greenhouse gases, as well as for corporate average fuel economy, in light-duty vehicle models in 2017-2025. As an example of the more tailored approach to applying the learning rate in this post-NHTSA regulatory impact assessment, note the way a less mature technology like air conditioner alternative refrigerants is treated in this table. This technology is considered to be initially subject to steep learning, with a consequent application of an initial 20% learning rate. After the initial period of steep learning (2016-2020), however, the EPA-NHTSA approach applies flat learning rates of 3% per year for five years, 2% per year for five years, then 1% per year for five years (U.S. Environmental Protection Agency 2012).

Table 3. Learning rate by technology package component

Technology	Steep learning	Flat learning	No learning
Engine modifications to accommodate low friction lubes			2012-2025
Engine friction reduction – level 1 & 2			2012-2025
Low drag brakes			2012-2025
Secondary axle disconnect		2012-2025	
Cylinder deactivation		2012-2025	
Air conditioner alternative refrigerant	2016-2020	2021-2025	
Air conditioner related hardware		2012-2025	

Source: (U.S. Environmental Protection Agency and U.S. Department of Transportation 2011)

[7] For traditional air pollutant regulatory impact assessments, the time period for production to double is usually two years, but this time period becomes longer for greenhouse gas regulatory impact assessments, which assume a greater role for alternatives to the internal combustion engine.

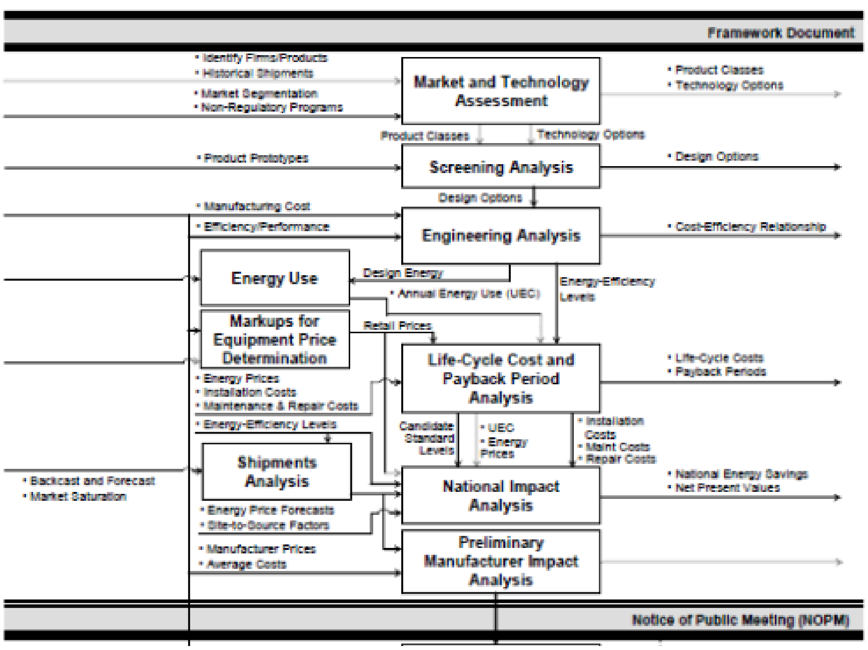
Note that the EPA-NHTSA approach includes sensitivity analyses to evaluate the impact of learning rate assumptions on projected prices. The basic sensitivity analysis approach is to bound the low, primary, and high side cost estimates via the use of a variety of learning rates.

3.2 Use of Learning Curves in Appliance MEPS

This section summarizes the DOE approach to incorporating learning curve-based cost adjustments in appliance minimum efficiency performance standards (MEPS) regulatory impact assessments, which the agency began to do in 2011, independent of the EPA-NHTSA approach.[8] The DOE approach is not a component-based approach like the EPA-NHTSA approach, but instead considers the learning curve in the context of the price of the full product.

a. General DOE Regulatory Impact Assessment Approach

The DOE has been tasked with consideration of Energy Conservation Standards – a form of MEPS – since 1979. The agency is required by statute to set forth MEPS that achieve the maximum improvement in energy efficiency given the constraints of technological feasibility and economic justification. The regulatory impact assessment approach addresses the requirement for economic justification through analyses of: life-cycle cost; economic impact on manufacturers; national benefits; impacts, if any, on utility companies; and impacts, if any, from lessening competition amongst manufacturers. Figure 6 provides an overview of the full regulatory impact assessment process for setting a new MEPS. Note that the DOE learning curve compliance cost adjustment approach has been a part of two of these analyses since 2011: (1) life-cycle cost and payback period analysis (LCC); and (2) national impact analysis (NIA).



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[8] Recall that the term "regulatory impact assessment" is used in this document in the manner that "regulatory impact analysis" is used in the academic and practitioner literatures on regulatory economics and cost-benefit analysis. We use this wording in order to avoid confusion with the Department of Energy's minimum efficiency performance standards (MEPS) technical support document (TSD) module titled "regulatory impact analysis" or "RIA," which primarily considers non-regulatory approaches to MEPS.

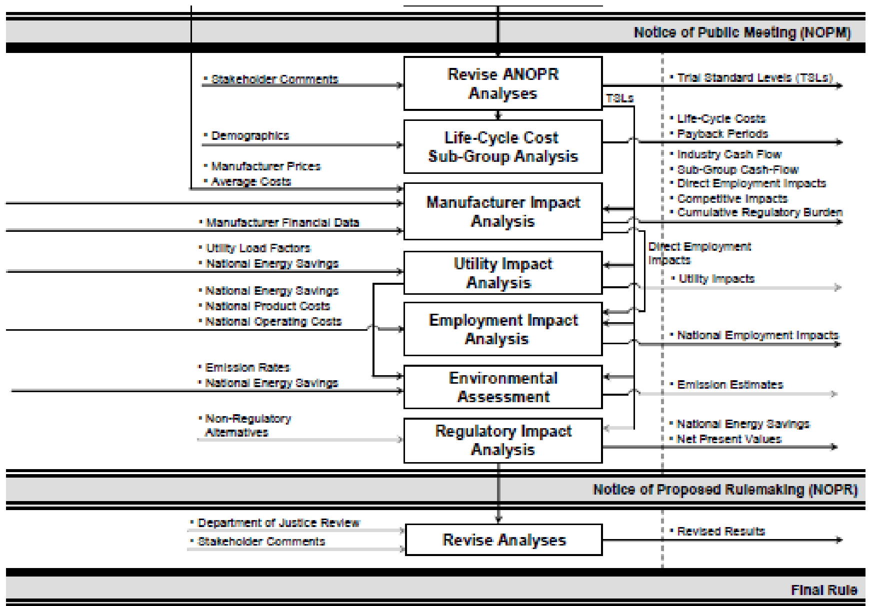

Figure 6: DOE regulatory impact assessment framework for MEPS.

The LCC analysis focuses on the economic impacts of MEPS on individual consumers. It estimates the present value of the total consumer expense over the lifetime of an appliance, including purchase and operating costs, with future operating costs discounted to the present (i.e., the analysis year). Purchase costs (also known in the regulatory impact assessment as the "total installed cost") are calculated by use of the following inputs: (1) the "baseline" manufacturer costs;[9] (2) the increases in manufacturing costs associated with meeting one of several proposed alternative efficiency standards; (3) the markups and sales tax increases associated with converting manufacturer costs to consumer product costs; and (4) the product installation costs to the consumer, which include labor, overhead, and miscellaneous materials and parts. Operating costs are estimated on the basis of energy consumption, based on product efficiency levels and usage conditions derived from data sources such as the Residential Energy Consumption Survey (RECS), as well as energy prices and trends, repair and maintenance costs, and assumed lifetime and discount rate distributions. All these costs are simulated for a sample of thousands of consumers using Monte Carlo simulation techniques, with the average results speaking to the cost-effectiveness of each efficiency level for consumers.

Meanwhile, the NIA focuses on the national energy savings and the present value to the nation of the total consumer costs and savings projected for the lifetime of products purchased at each potential standard level over the first thirty years after the appliance MEPS takes effect. Different scenarios in the NIA (depending on the product) allow variation in the market share of a range of models with different efficiency levels over time, including a scenario in which model market shares for different efficiency levels remain fixed with no change over time. The basic effect incorporated in most scenarios, however, is that from the date the MEPS becomes effective, the market share of the models with efficiency levels worse than the MEPS are zeroed out, and their market shares are added to those of models with efficiency levels that comply with the MEPS.

[9] The manufacturer selling price includes direct manufacturing production costs (labor, material, and overhead), non-production costs (sales, general, and administration; research and development, and interest), and profit.

Note that both the LCC and the NIA are linked to product cost-efficiency information derived from manufacturer interviews and product teardown analyses conducted by an independent contractor. Three approaches are used by that contractor to determine the cost-efficiency relationships of relevance to potential MEPS: (1) a design-option approach, which calculates the incremental costs of adding specific design options to a baseline model; (2) an efficiency-level approach, which calculates the relative costs of achieving increases in energy efficiency levels without regard to the particular design options used to achieve such increases; and/or (3) a reverse engineering or cost-assessment approach, which involves a "bottom-up" manufacturing cost assessment based on a detailed bill of materials derived from teardowns of the product being analyzed. The ultimate methodology is selected on a product-by-product basis, given the design options under study and any historical data that DOE can draw on.

b. Chronology of the Use of Learning Curves in MEPS Regulatory Impact Assessments

As depicted in Table 4, the DOE has applied learning curves to regulatory impact assessments for at least half a dozen product MEPS dating back to 2011. Before incorporating learning curves into its regulatory impact assessments, the DOE did some preliminary investigation into learning curves, which resulted in the publication of a Notice of Data Availability (NODA) in February 2011, shortly after OIRA issued official guidance on the Obama administration's first term cost-benefit executive order, EO 13563.

Table 4: MEPS regulatory impact assessments incorporating learning curve cost adjustments

Date	Rulemaking Activity	Product
2011	Final Rule	Residential Refrigerators, Refrigerator-Freezers, and Freezers
2011	Direct Final Rule	Residential Clothes Dryers and Room Air Conditioner
2011	Direct Final Rule	Residential Central Air Conditioners, Heat Pumps, and Furnaces
2012	SNOPR	Microwave Ovens (Standby Power)
2012	Direct Final Rule	Residential Clothes Washers
2012	Direct Final Rule	Dishwashers

Source: Timeline is based on appliance policy regulatory impact assessments by DOE in (2011a; 2011b; 2011c; 2011d; 2012)

c. DOE Framing of the Learning Curve Approach

In each of the DOE's regulatory impact assessments that include learning curve-based cost adjustments, to date, learning curves have been discussed in four places: in the main document sections on the LCC and NIA, as well as in two appendices that are tied to these chapters. The DOE framing of the learning curve approach generally lacks the specific citations to the management literature and the underlying phenomenon that are included in the EPA-NHTSA approach, although a research article developed for the energy policy literature concurrently with the regulatory impact assessment chronology provided in Table 4, above, includes a brief literature review and introduction to the concept (see Desroches, Garbesi et al. 2013). Within the regulatory impact assessment documents themselves, however, the writing on the DOE approach tends to equate the long-term declines observed in appliance prices with learning as well as experience curves, and does not discuss the complex factors that underlie the learning curve phenomenon. At times, the writing also explains that the DOE approach continues historical trends in prices in order to capture potential long-term changes in future prices (linked to projected shipments), but it does not acknowledge the limitations of doing this.

d. DOE Derivation and Application of Learning Curves to Adjust Cost Projections

The basic DOE approach to incorporating learning curve-based cost adjustments in appliance MEPS regulatory impact assessments has two parts, which we discuss in more detail below. First, the DOE approach fits a learning curve to past data for the whole of a given product that is the subject of the regulatory impact assessment. Second, it uses that learning curve to derive a multiplier for a part of the cost projections for the given product under both a business-as-usual case as well as a case in which a new MEPS is set for the product (for more information, see Desroches, Garbesi et al. 2013).

1. Derivation of Learning Curves

In deriving product-specific learning curves, the DOE approach gathers past data on: (1) a price-based proxy for product manufacturing costs; and (2) a shipments-based proxy for product production. Although both of these proxies are imperfect, they have attributes of internal consistency and data availability that make them appealing. The data source generally used for the price proxy for manufacturing cost is the Producer Price Index (PPI) series that contains the given product.[10] Although in some cases, a PPI series is available for a specific product, in other instances a PPI series only exists for a set of products that includes the specific product (e.g. household laundry equipment, which includes the clothes washers of interest for MEPS, etc.). The disadvantage of using a more aggregate series is that it assumes that product price trends of the individual products within the set contained in the series are generally consistent with the trend for the set of products as a whole. Several data sources are generally drawn from in order to derive a U.S. shipments-based proxy for past annual U.S. manufacturing output of the given product. These shipments data – which include data on U.S. domestic production plus imports – come primarily from manufacturing trade associations (e.g., the Association of Home Appliance Manufacturers (AHAM); Gas Appliance Manufacturers Association; the Air Conditioning, Heating, and Refrigeration Institute; etc.), as obtained either directly through data request or through industry publications.

Using these data, the DOE approach follows Equation 1 (with slightly different notation) and performs simple least squares power law fits in order to derive the key parameter b that links the traditional and estimation functional forms of the learning curve to the progress ratio and the learning rate. Table 5 presents the b parameters derived for each appliance in the chronology of regulatory impact assessments presented in Table 4, above.

[10] The PPI is one of the oldest continuous systems of statistical data compiled by the U.S. federal government. In it, the Bureau of Labor Statistics (BLS) reports the average change in the selling prices received by domestic producers for their output. The prices included in the PPI are from the first commercial transaction for many products and some services. Desroches, Garbesi et al. (2013) points out that there is an attempt within the PPI to filter out "physical changes (such as capacity, premium features, government-mandated features, etc.) in the product that affect the price."

Table 5: Parameters derived in the DOE approach to measure the rate that prices decline as cumulative output increases

Product	PPI Series	b
Residential Clothes Dryers	Household laundry equipment	0.775
Room Air Conditioner	Room air-conditioners and dehumidifiers	0.710
Residential Refrigerators and Freezers	Household refrigerators and freezers	0.755
Warm Air Furnace	Warm air furnaces	0.527
Unitary Air Conditioners	Unitary air-conditioners, except air source heat pumps	0.288
Microwave Ovens[b]	Electric cooking equipment	0.492
Residential Clothes Washers[a]	Household laundry equipment	-0.025
Dishwashers	Miscellaneous household appliances	0.436

[a] Note that an exponential functional form was used for clothes washers, unlike the other products.
[b] The limited number of years that a PPI series is available for microwaves only is why the DOE approach uses the longer, more aggregate PPI series of electric cooking equipment to proxy microwave prices.

2. *Application of Learning Curves*

The DOE approach uses the parameter *b* estimates above to derive a multiplier that it incorporates into the cost calculations performed for both the LCC and the NIA. Note that there is not much variation in how this multiplier is applied for a given product under the conditions of business-as-usual efficiency and MEPS-compliant efficiency. We explain the basic approach through the following equations.

First, the parameter *b* is estimated with price as a proxy for cost. Equation 5 makes this explicit by converting Equation 1 and Equation 2 to indicate the use of price as a proxy for cost.

Equation 5: Converting Equations 1 and 2

$$P_t = P_0 * X_t^{\ -b}$$
$$\ln(P_t) = \ln(P_0) - b * \ln(X_t)$$

Where:

P_t = price in year *t* (used as a proxy for cost, or *C* in Equations 1 and 2)
P_0 = initial PPI value (used as a proxy for the cost of the first item made, or C_0 in Equations 1 and 2)
b = a parameter that measures the rate costs are reduced as cumulative output increases

and

$X_t = \sum_{s<t} Q_s$ = cumulative production in year *t* (using the notation for production in Figure 2)

Where:

s = an index value for the time prior to year *t*, set at 1 in the first year of shipments data
Q = an annual unit of production

The parameter *b* is estimated using the above specification. The estimated *b*, denoted by *b_hat*, is then used to calculate the price factor index the DOE approach uses to adjust its cost estimates in each year. This price factor index is set equal to 1 in the year the regulatory impact assessment is conducted; in future years, the price factor index in a given projection year is a function of *b_hat* and the projected cumulative production up to that year, based on forecasts of annual shipments.

Equation 6: Price factor index applied in the DOE approach to learning curve-based cost adjustment

$$PF_t = PF_{t-1} * \left(\frac{X_t}{X_{t-1}}\right)^{-\hat{b}}$$

Where:

PF_t = price factor in year *t* (*PF* = 1 in the analysis year)

X_t = cumulative production through year *t-1* (proxied by U.S. shipments)

$\hat{b}$= *b_hat* = estimated parameter that measures the rate costs are reduced as cumulative output increases

Equation 6 is used to generate a series of price factors for all years used in the cost-benefit calculations into the future. The projected price in year *t* can be calculated by multiplying the analysis period price *(P_0)* by the price factor for year *t*. This is shown in Equation 7.

Equation 7: Projected price in year *t*

$$P_t = P_0 * PF_t$$

As mentioned above in the description of the general regulatory impact assessment framework followed by the DOE in establishing MEPS, the LCC analysis focuses on the economic impacts of MEPS on individual consumers. It derives a payback period (*PBP*) for a given product MEPS which reflects how long it will be before a consumer recovers the assumed higher purchase price of a more energy efficient, MEPS-compliant product through lower product operating costs. The *PBP* is more formally defined as the ratio of the difference in total installed cost between a more and less (baseline) energy efficient design over the difference in annual operating expenses between a more and less (baseline) efficient product. The following equations demonstrate how the learning curve price factor index is used in the equations that contribute to the PBP for a given product (for the original notation used in the MEPS regulatory impact assessments, please see Appendix A).

First, the payback period (PBP) is calculated for a product purchased on the date the standard becomes effective (the MEPS effective date, or *StDate*), as shown in Equation 8.

Equation 8: LCC payback period

$$PBP = \frac{TIC_{e,t=StDate} - TIC_{b,t=StDate}}{O_b - O_e}$$

Where:

$TIC_e =$

$\text{Total installed costs for the efficient model purchased on the MEPS effective date } StDate$

$= MC_{e,t=analysis} * MU_e * PF_{t=StDate} + IC_e$

TIC_b

$= \text{Total installed costs for the baseline model purchased on the MEPS effective date } StDate$

$$= MC_{b,t=analysis} * MU_b * PF_{t=StdDate} + IC_b$$

And

O_b, O_e = per-period operating expenses for the baseline and efficient models, respectively
$MC_{b,t=analysis}$, $MC_{e,t=analysis}$ = manufacturing costs for the baseline and efficient models, respectively, calculated in the year of the MEPS analysis
$PF_{t=StDate}$ = price factor in year *t*, where *t* is the year the MEPS comes into effect
MU_b, MU_e = markup for the baseline and efficient models, respectively
IC_b, IC_e = installation costs for the baseline and efficient models, respectively

In the NIA part of the MEPS regulatory impact assessment, by contrast, the focus is on the national energy savings and the present value to the nation of the total consumer costs and savings projected for the lifetime of products purchased at each potential standard level over the first thirty years after the appliance MEPS takes effect. In the NIA analysis, the net present value (*NPV*) of the MEPS is defined as the difference between the present value of operating cost savings from the more efficient product and the present value of increased total installed costs from that more efficient product; these total installed costs include the purchase price and installation costs (note that as in the LCC analysis, the former is subject to the price factor adjustment while the latter is not). The following equation demonstrates how the learning curve price factor index affects the NPV for a given product (for the original notation used in the MEPS regulatory impact assessments, please see Appendix A).

Equation 9: NIA net present value analysis, including the influence of the price factor index

$$NPV = \sum_y \left\{ \sum_V (S_{b,V,y} * O_{b,V,y} - S_{e,V,y} * O_{e,V,y}) \right\} * r_y - \sum_y Q_y * \left\{ \sum_j \left(CP_{e,j,y} * MS_{e,j,y}\right) - \left(CP_{b,j,y} * MS_{b,j,y}\right) \right\} * PF_y * r_y$$

Where:

V= vintage year (year a product was purchased)
y = year in the forecast
j = efficiency level of product types in the market
$O_{b,V,y}$, $O_{e,V,y}$ = operating expenses for the baseline and efficient models of vintage V as incurred in year y, respectively
$S_{b,V,y}$, $S_{e,V,y}$ = existing stock of the baseline and efficient models of vintage V in year y, respectively
$CP_{b,j,y}$,$CP_{e,j,y}$ = consumer product cost for the baseline and efficient models of efficiency level j purchased in year y, respectively
$MS_{b,j,y}$, $MS_{e,j,y}$ = market share of the baseline and efficient models of efficiency level j purchased in year y, respectively
r_y = discount factor in year y
Q_y = quantity of shipments in year y
PF_y = price factor index in year y

The key insight here is that in both Equation 8 and Equation 9, the price factor index applies to both the baseline and the efficient model, which tends to reduce the strength of its effect. This is particularly true in the NIA analysis.

Note that the DOE, like the EPA, conducts sensitivity analyses to evaluate the impact of various model assumptions on projected prices. Unlike the EPA, which primarily varies the progress ratios in its sensitivity analyses, the DOE primarily varies the data that can be used to calculate the parameter *b*.

4. Discussion

4.1 Currently Available Techniques

In February 2011, when OIRA called for federal agencies "to use the best available techniques to quantify anticipated present and future benefits and costs as accurately as possible," including "identifying changing future compliance costs that might result from technological innovation or anticipated behavioral changes," those best-available techniques were not obvious. Indeed, DOE's NODA shows the range of options that were considered possible at the time:

(1) fitting an experience curve to available data on the cost trends for equipment or technologies that are components of a given efficiency design option in order to forecast the future cost of that design option;

(2) using experience curve cost trends for the analyzed product as a whole, in order to project both the price of that item as well as the price of the more efficient product options;

(3) applying an experience curve cost trend derived from an analogous product, equipment, or grouping of products or equipment (which includes the analyzed product) in order to project both the price of the analyzed product as well as the price of the more efficient product options; and

(4) using experience curve parameters or ranges of parameters drawn from published review articles that are applicable to certain classes or groups of products or equipment (which include the analyzed product) in order to project both the price of the analyzed product as well as the price of the more efficient product options (U.S. Department of Energy 2011).

When assessing the "best available" options, a combination of the first and fourth option can be considered to be most widely available, given the oeuvre of regulatory impact assessments conducted by the U.S. federal government. This is because of the extensive track record of the EPA, and later NHTSA, in applying a learning curve-based adjustment to the direct costs of the components of compliant technology packages. Access to significant data and expertise allows the EPA-NHTSA approach to consider each component's degree of diffusion in the marketplace and likely potential to see steep, flat, or no learning effects. The agencies are then able to apply associated learning rates, as derived from a classic review article, to estimates of the long-term direct costs (e.g., materials and labor) and learning curve relevant consumer costs (i.e., vehicle purchase price rather than operating cost) of achieving the proposed regulation (see USEPA and

USDOT 2011). It is important to recall that the indirect costs of compliance (e.g., R&D, corporate operations, marketing, etc.) are not subject to the learning curve-based adjustment.

Note that the EPA-NHTSA approach applies learning rates over only a limited time period. The agencies' reasoning follows from the assumption that a new regulation will serve as the initial condition for the production of a new, regulatory compliant vehicle. In an implicit acknowledgement of the learning curve literature's finding that learning effects cannot be estimated with accuracy for more than a few doublings of cumulative production, the EPA-NHTSA approach uses the agencies' understanding of the production patterns of the vehicle industry to make the assumption that the production of the new vehicle model will double in two years.

For a variety of reasons related to data and fit with existing institutional arrangements, the DOE has, thus far, not adopted a similar component-based approach, and instead has employed a combination of the second and third options listed above. It derives a learning curve parameter from past price and shipments data for the whole product to be subject to MEPS, and uses the resulting product-specific parameter plus projected shipments to generate a price factor index it uses to adjust the costs of both baseline and more efficient products. When the available price data is not limited to the regulated product itself, the DOE approach sometimes uses more aggregate price data when it includes the regulated product.

4.2 Assessing Prediction Accuracy

The primary reason why regulatory reform advocates and OIRA are interested in a better accounting for technological change in regulatory impact assessments is prediction accuracy. This raises the question: what is the relative accuracy of the learning curve-based regulatory impact assessment cost adjustment technique, as it has been applied in the EPA-NHTSA approach and the DOE approach? The answer should emerge from an analysis that compares the projections made using the agency's traditional and learning curve-based cost adjustment techniques, as benchmarked against the actual price of the regulated product. Such an analysis is difficult to conduct for contemporary regulatory impact assessments due to lags. But it should be possible to investigate past regulatory impact assessments using this method for gauging prediction accuracy.

Unfortunately, as has been pointed out in the regulatory economics literature, there is a dearth of retrospective reviews of regulation to draw from. We were unable to locate any retrospective reviews of the EPA-NHTSA regulatory impact assessment cost projections, for example, either by searching the literature or speaking with economists with long careers at the EPA and OMB. In addition, the Harrington, Heinzerling et al. (2000) paper does not include the appropriate vehicle emissions and CAFE regulatory impact assessments in its review of 28 examples of environmental, health, and safety regulation.

We were, however, able to complete a first-order review of the improvements in prediction accuracy the DOE approach provides when compared to the traditional DOE regulatory impact assessment approach for MEPS of holding costs constant throughout the analysis period. Our review leveraged heavily Dale, Antinori et al. (2009), which investigated trends in retail appliance prices and compared those prices to DOE MEPS projections, finding that MEPS projections tended to overestimate retail prices. We performed a simple analysis comparing: (1) the DOE price projections from previous rulemakings, as presented in the Dale, Antinori et al. (2009) paper (here called the "constant price assumption"); (2) observed retail prices for those products, as presented in the Dale, Antinori et al. (2009) paper (here called the “actual price”); and (3) price estimates that could have been done at the time of the original rulemakings under a hypothetical condition in which the current DOE approach to adjusting costs using a learning curve based approach was available (here called the “PPI-based price trend projection”). Figure 7 presents this comparison, as well as +/- error bars of 25% of the actual price, following the approach to determining over- and under-estimation of the costs of compliance in regulatory impact assessments followed by the seminal Harrington, Morgenstern, et al (2000) paper. For more detail on the method we followed, see Appendix B.

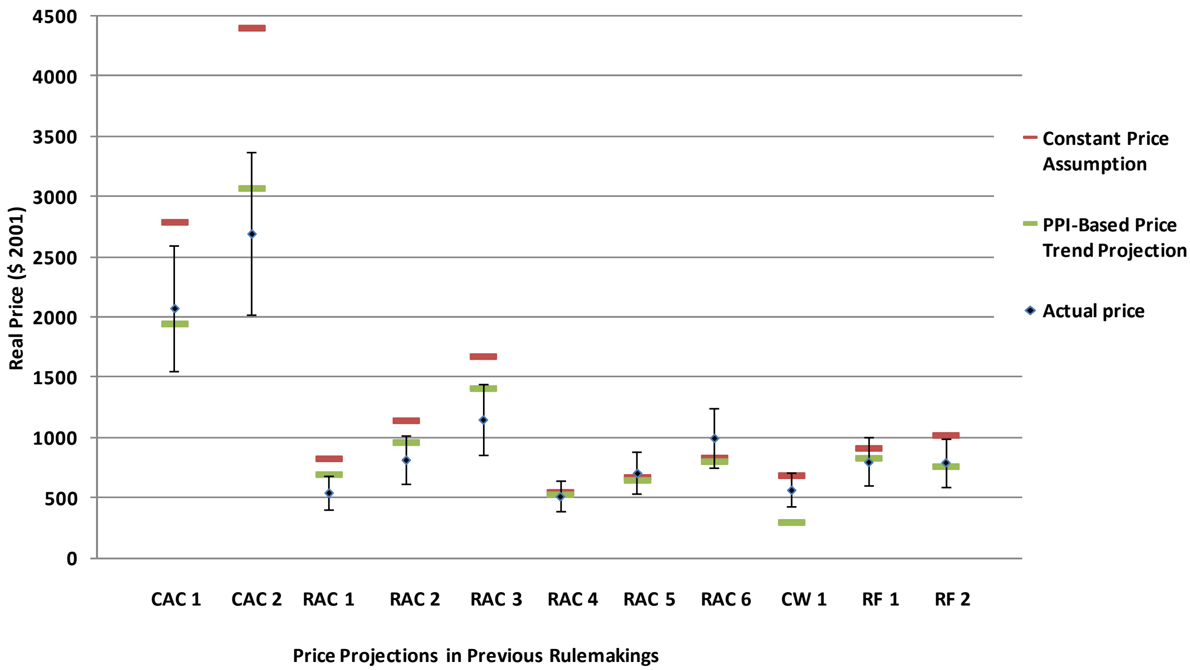

Figure 7: Comparison of prediction accuracy between constant price assumption and PPI-based price projection

Note: CAC = Central air conditioning, for the MEPS analyzed in 1982 and effective in 1988 (1 = Small, or <39 kBtu; 2 = Large, or >39kBtu); RAC = Room air conditioning (1-3 are for the MEPS analyzed in 1982 and effective in 1987, with 1 = Small, or 8 kBtu; 2 = Medium, or 14 kBtu; and 3 = Large, or 20 kBtu; 4-6 are for the MEPS analyzed in 1990 and effective in 1993, with 4 = Small, or 8 kBtu; 5 = Medium, or 14 kBtu; and 6 = Large, or 20 kBtu; CW = Clothes Washers, for the MEPS analyzed in 1990 and effective in 2001 (1 = Standard 115 v, 2.6 ft^3); RF = Refrigerators (1 = Top-mount, auto-defrost, for the MEPS analyzed in 1989 and effective in 1994; 2 = Top-mount, auto-defrost, for the MEPS analyzed in 1991/95 and effective in 2001). Observed prices are derived from Dale et al (2009). In this paper, central AC prices are described as “retail price,” and price factor estimates are accordingly applied. If these central AC prices in fact include an installation cost, the price factor should only be applied to the retail price, and the accuracy under the price trend method would be somewhat less than this analysis suggests (although still more accurate than under the constant price assumption). All other product prices are described as “retail price” as well, but as none of these products are expected to have substantial installation costs, any error in price definition is less likely to impact these estimates of price trend method accuracy. Error bars on the observed price (2001$) are +/- 25% of the observed price, in keeping with the approach used in Harrington, Morgenstern, et al (2000).

In most of the examples in Figure 7, we observe that the PPI-based price trend projection is closer to the actual price than the constant price assumption. Stated in another way, the current

DOE approach to applying a whole-product learning curve-based cost adjustment in regulatory impact assessments appears to have generally higher prediction accuracy than the agency's previous constant-cost assumption based regulatory impact assessment approach. We believe that there is still room to refine the DOE approach, however, particularly with respect to improving its prediction accuracy and aligning it better with economic theory.

4.3 Considerations for Developing and Refining the Technique

As the regulatory community reflects on whether and how to adopt a learning curve-based cost adjustment technique as a "best practice" in regulatory impact assessment, a number of design considerations fall out of the literature and past experience with the EPA-NHTSA approach and the DOE approach. We recommend that agencies think carefully about: (1) how they derive one or more learning curves to use in cost adjustments; (2) how they intend to apply adjustments within their existing cost models; and (3) possibly iterating the approach they develop based on a benchmark analysis against real world prices for regulated products.

In deriving one or more learning curves, agencies should keep in mind the key finding in the literature that there is considerable variation in progress ratios. Briefly, the literature shows that within-technology variation has been observed at roughly the same levels as between-technology variation, with many potential explanatory factors for that variation, which include organizational forgetting; employee turnover; transfer of knowledge across products, business lines, and organizations; management practices; and volatility in the competitive environment. As the aspects of a product that enable it to achieve regulatory compliance are not necessarily integrated within the regulated industry, but may be supplied by external business lines, firms, or industries, it is likely that focusing learning curve derivation on the specific compliance-enabling components of the product under regulatory consideration will more appropriately account for potential progress ratio variation.[11] This is especially true when considering that the degree of "newness" of the compliant components could affect the shape of the learning curve (see Wiersma 2007). Thus, not only should agencies try to isolate the compliance-enabling components of a technology, they should also try to assess the unit costs, degree of maturity, and level of diffusion of those components, in order to consider the slope of the appropriate learning curve to derive either from past experience or the literature. Note that when considering past experience in deriving learning curves, it is important to be transparent about the rationale for decisions regarding the years of experience considered appropriate, as well as any analytical proxies that might be required to substitute for unit cost and production (e.g., retail price, the PPI, shipments data, etc.). This will allow greater explanation of the limitations of the analysis.

In applying learning curve-based cost adjustments, it is important to remain true to the product under regulatory consideration. For example, the timing of product development – from its initiation to its obsolescence under typical and regulatory-impacted conditions – is very important to assumptions about the rate at which cumulative production doubles. In turn, this rate is important to the potential of a learning curve-based cost adjustment to improve the prediction accuracy of a regulatory impact assessment, given the warning in Weiss (2010) that projecting beyond three or four doublings of cumulative production can result in serious under- or over-estimation of production costs. As another example, being true to the industry conditions of the product under regulatory consideration will help protect the analysis from the effect of drawing

[11] Kantor and Zangwwill (1991) provides a useful assessment of the appropriate functional form to use in deriving component-based learning curves.

false conclusions for future trends from potentially time-specific events in past experience (e.g., the impact on the costs of a regulated product of industry consolidation, outsourcing, policy changes, etc.). Note that the architecture of the cost models employed in an agency's regulatory impact assessment framework are also important to keep in mind, as they affect the ease of adjusting costs via a learning curve-based approach.

As the DOE works to refine the learning curve-based cost adjustment technique it uses in its MEPS regulatory impact assessments, we recommend that it consider undertaking a research program directed toward developing a component-based approach. As a first research avenue to explore, we believe that developing a component-based approach would be facilitated by leveraging some of the data currently used to inform the Engineering Analysis and Manufacturer Impact Analysis of the existing MEPS regulatory impact assessment framework. These framework sections are based on proprietary business information on the components required for higher efficiency, the cost of those components (i.e., the incremental cost of higher efficiency), and the product cycle times of regulated products, although leveraging these data may be difficult because of institutional issues. Another potentially fruitful research avenue might be to obtain price data and a sense of technological change in the MEPS-covered industries through collaborative research with the Bureau of Labor Statistics, which: (1) has micro-level survey data on producer prices that researchers can access under controlled conditions; (2) publishes indices of prices for many components of technologies of interest to appliance energy efficiency (e.g., insulation); and (3) makes quality adjustments to producer prices (in order to maintain the PPI) which could be used as a proxy for the rapidity of technological change in an industry. A third potential research avenue would be to analyze the intellectual property underlying regulated products, in consultation with industry experts. Armed with a combination of data obtained through any of these avenues, analysts could undertake an assessment of the maturity of MEPS compliance-enabling components, or at least derive boundary conditions in which all key components could be considered very new or very mature, with implications for cost adjustment based on steep or flat learning curves, respectively.

Note that even a simple understanding of the level of product redesign required to achieve a standard could justify the application of a steeper or flatter learning curve-based cost adjustment to the whole product, perhaps drawing the relevant learning curve from a meta-analysis of the literature, in the manner of the EPA-NHTSA approach. The advantage of this is that the standard cost model used by the DOE in conducting regulatory impact assessments for MEPS – at least in the case of the NIA – already has in place different scenarios for the diffusion of models of different efficiencies in the marketplace, so applying varying price factors to those products would be relatively straightforward.

We also recommend that the DOE consider three additional research tasks. First, it should develop more expertise on the industry conditions of the products it regulates, including evidence-based model cycle times and a better understanding of the factors that underlie the long-term downward price trends that have been observed in appliances and other products. Second, it should explore the options for retrospective review in more regulated products, beyond those captured in Dale, Antinori et al. (2009), particularly as the agency develops MEPS for untraditional products. Third, it should focus more attention on the exceptional products in Figure 7 in which the learning curve technique, as currently applied, would have led to an underestimation of future product prices. Besides the fact that such situations pose potentially high political costs to a regulatory agency and should generally be avoided, there may be generalizable issues for regulatory impact assessment that could be learned from these products.

5. Acknowledgements

The authors would like to thank Anna Spurlock and Larry Dale for their substantive advice and assistance. In addition, we would like to thank Steven Meyers, Hung-Chia Yang, Greg Rosenquist, Louis-Benoit Desroches, Alan Sanstad, and Alex Lekov for their feedback.

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Appendix A: Learning Curve-Based Cost Adjustment Equations in DOE Regulatory Impact Assessments

The following equations are incorporated in final rules for DOE MEPS over the last year (for the products of dishwashers and clothes washers).

Equation 10: Payback period in the LCC

$$PBP = \frac{\Delta IC}{\Delta OC}$$

Where:

ΔIC = difference in total installed cost between the more energy efficient design and the baseline design

ΔOC = difference in annual operating expenses

Equation 11: LCC total installed cost for products with baseline efficiency

$$IC_{BASE} = CPC_{BASE} + INST_{BASE}$$

Where:

$$CPC_{BASE} = COST_{MFG} \times PF_{ED} \times MU_{OVERALL\_BASE}$$

And:

IC_{BASE} =	baseline total installed cost,
CPC_{BASE} =	consumer product cost for baseline models,
PF_{ED} =	price factor of the effective date of the standard,
$INST_{BASE}$ =	baseline installation cost,
$COST_{MFG}$ =	manufacturer cost for baseline models, and
$MU_{OVERALL\_BASE}$ =	baseline overall markup (product of manufacturer markup, baseline retailer or distributor markup, and sales tax).

Equation 12: LCC total installed cost for products with higher efficiency

$$IC_{STD} = CPC_{STD} + INST_{STD}$$

Where:

$$CPC_{STD} = (CPC_{BASE} + \Delta CPC_{STD}) + (INST_{BASE} + \Delta INST_{STD})$$

And:

$$\Delta CPC_{STD} = \Delta COST_{MFG} \times PF_{ED} \times MU_{OVERALL\_INCR}$$

And:

IC_{STD} =	standard-level total installed cost,
CPC_{STD} =	consumer product cost for standard-level models,

$INST_{STD}$ = standard-level installation cost,
CPC_{BASE} = consumer product cost for baseline models,
ΔCPC_{STD} = change in product cost for standard-level models,
$INST_{BASE}$ = baseline installation cost,
$\Delta INST_{STD}$ = change in installation cost for standard-level models,
$\Delta COST_{MFG}$ = change in manufacturer cost for standard-level models, and
$MU_{OVERALL\_INCR}$ = overall incremental markup (product of manufacturer markup, incremental retailer or distributor markup, and sales tax)
PF_{ED} = price factor of the effective date of the standard.

Equation 13: NIA net present value

Net Present Value = Present value of operating cost savings - Present value of increased total installed costs (including purchase price and installation costs)

Mathematically, this is:

$$NPV = \sum OCS_y \times DF_y - \sum TIC_y \times DF_y$$

Where:

OCS = Total annual savings in operating costs each year summed over vintages of the product stock, $STOCK_V$,
DF = Discount factor in each year,
TIC = Total annual increases in installed cost each year summed over vintages of the product stock, $STOCK_V$,
$STOCK_V$ = stock of products of vintage V that survive in the year for which DOE calculated annual energy consumption,
V = year in which the product was purchased as a new unit;
y = year in the forecast.

DOE calculates the total annual increases in consumer product cost by multiplying the number or shipments of the given product class (by vintage) by its per-unit increase in consumer product cost (also by vintage), accounting for the annual price factor. The calculation of total annual product cost increases is represented by the following equations:

Equation 14: Annual product cost increases in consumer product costs, as used in the NIA

$$TIC_y = \sum SHIP_y \times UTIC_y$$

Where:

$SHIP_y$ = shipments of products in year y; and

$UTIC_y$ = annual per-unit increase in installed product cost in year y.

And:

$$UTIC_y = \left(\sum_{j=1} PRICE_{STD,j} \times SHARE_{STD,j,y} - \sum_{j=1} PRICE_{BASE,j} \times SHARE_{BASE,j,y} \right) \times PFy$$

Where:

$UTIC_y$ =	annual per-unit increase in installed product cost in year y,
$PRICE_{STD,\,j}$ =	average consumer product cost under the standard of products at efficiency level j,
$SHARE_{STD,j,y}$ =	market share by efficiency level, j, in year y, under the standard,
$PRICE_{BASE,\,j}$ =	average consumer product cost in baseline case of products at efficiency level j,
$SHARE_{BASE,j,y}$ =	market share by efficiency level, j, in year y, in baseline case,
PF_y =	price factor in year y,
j =	product efficiency level,
y =	year in the forecast.

Appendix B: Retrospective Review Method Used to Consider the Accuracy of the DOE Approach

There are growing calls for analysts to publish more retrospective reviews of regulation and regulatory impacts assessments, as there has been a general paucity of such reviews, despite the valuable lessons they can provide. One of the few published examples of a retrospective review of MEPS regulatory impact assessments is Dale, Antinori et al. (2009). This paper compared DOE regulatory impact assessment cost predictions against retail price data, and demonstrated that the method that was traditionally used by the DOE to project the costs of achieving MEPS – which involved holding product prices constant over the period in which the standard would be in effect – was generally leading to overestimating the costs of efficient appliances.

In considering how we could do a first order assessment of the changes in prediction accuracy that might result from the new DOE cost projection approach, which incorporates a learning curve-based adjustment, we looked to the Dale, Antinori et al. (2009) paper to provide a useful methodology. However, since the small set of MEPS with the new cost adjustment, detailed in Table 4 in the body of this report, have not been in effect long enough for us to assess them with confidence, we realized that the Dale, Antinori et al. (2009) paper could also be useful to us in other ways. We decided to revisit the data and analyses in that paper in order to consider how accurate the DOE MEPS regulatory impact assessments studied in it would have been in a hypothetical scenario in which those assessments employed the new approach, rather than the previous, constant-cost approach.

As depicted in Figure 7 in the body of this report, our first order assessment showed that the new method was generally more accurate than the old method, although when benchmarked against a +/- error bar of 25% of the observed retail price, we believe there is still room to improve the method. In this appendix, we provide more detail on the calculations that went into this analysis.

Methodology

Table 6 summarizes the key inputs that went into our analysis, which draw from both recent regulatory impact assessments and the Dale, Antinori et al. (2009) paper. We focus our analysis on products that are shared by both sources. From the Dale, Antinori et al. (2009) paper, we take the predicted price, held constant, to be the “constant price assumption” price in Figure 7, and we use the realized market price to be the “actual price” in Figure 7. Using the analysis year and effective date of the previous MEPS, as detailed in Dale, Antinori et al. (2009), we limit the data that can inform the derivation and application of the learning curve-based cost adjustments in the current regulatory impact assessment approach. Thus, the PPI and shipment series used to construct appropriate learning curves are limited to the data available in the context of the previous MEPS (e.g. for the 1991 refrigerator rule, the data set includes 1977, the first year the PPI series is available, and continues through 1991, the year of MEPS analysis).

Table 6. Key inputs by source

<table>
<tr><th>Dale, Antinori et al. (2009)</th><th>Recent regulatory impact assessments</th></tr>
<tr><td>Product categories: Room Air Conditioners (room AC), Central Air Conditioners (central AC), Refrigerators, Clothes washers
Predicted (constant) prices
Realized market prices
Analysis year and effective date</td><td>Product categories: Room Air Conditioners (room AC), Central Air Conditioners (central AC), Refrigerators, Clothes washers
Producer price index series (PPI)
Product shipments
Price adjustment method</td></tr>
</table>

Using these data, we followed Equation 5 and performed simple least squares power law fits akin to that used in the DOE approach on current products in order to derive the key parameter *b* that links the traditional and estimation functional forms of the learning curve to the progress ratio and the learning rate. Table 7 presents the *b* parameters derived for each appliance in the chronology of regulatory impact assessments presented in Table 4 in the main body of this document. In the cases in which Dale, Antinori et al. (2009) models more than one MEPS for a product (i.e., room air conditioners (Room AC), refrigerators) , we provide two parameters for that product in the table because the timing of each rule affects the PPI and shipments data series used to fit learning curves on the data.

Table 7. Parameters derived in the DOE Approach to measure the rate that product Prices Decline as Cumulative Output Increases, listed by product and rulemaking analysis year in Dale, Antinori et al. (2009)

Product	Rulemaking Analysis Year	*b*
Central AC	1982	0.539
Room AC	1982	0.789
Room AC	1990	0.516
Clothes Washer	1990	0.539
Refrigerators	1989	0.422
Refrigerators	1991/95	0.411

For our validation exercise, we would ideally compare price projections for individual years against market prices for those years, but in leveraging Dale, Antinori et al. (2009), we were limited to its presentation of market prices as an average price for the time period between the year the rulemaking analysis was conducted and the effective date of the standard. This required us to adjust the reasoning underlying the price factor in the DOE approach to using learning curves to adjust cost estimates.

Assuming a constant number of shipments per year, then the price factor in each year between the analysis date and the effective date of the standard is constant. Denote this per-year price factor as PF. Using this price factor, the price projection in any given year T periods into the future can be expressed as a function of the analysis year (t=0). This is expressed in Equation 15.

Equation 15: Price projection T years from the analysis period[12]

$$P_T = P_0 * PF^T$$

Where:
P_T = the price projection *T* years from the analysis period
P_0 = the price in the analysis period
PF = the price factor (assumed constant between year 0 and year *T* due to an assumption of constant shipments)

The average annual projected prices from year *t*=1 to year *t*=*T* can be readily derived from this. Thus, we can project the average price between the year following the analysis year and the year of the standard by multiplying the analysis year result, as shown in Equation 16:

Equation 16: The average projected price from year *t*=1 to year *t*=T

$$P_{avg} = P_0 * \frac{(PF + PF^2 + PF^3 + \cdots + PF^T)}{T}$$

Table 8 presents the price factors calculated for each product and original rulemaking analysis year.

Table 8: Estimated price factors by product and rulemaking

Product	Analysis Year	Price Factor (*PF*)
Central AC	1982	0.898
Room AC	1982	0.943
Room AC	1990	0.982
Clothes Washer	1990	0.853
Refrigerators	1989	0.969
Refrigerators	1991/95	0.917

Table 9 presents the average projected prices estimated using these price factors, in keeping with Equation 16. Within a single analysis year, the same price factors are applied to all sub-types within a product category (e.g. large, medium, and small capacity room AC).

Table 9: Estimated retail price by product and rulemaking

[12] We held installation costs of the products at zero, in keeping with their considerably smaller influence on the cost of compliance with MEPS than the total costs confronting consumers at purchase. This decision was also in keeping with conducting this analysis at a first-order level.

Product	Description	Analysis Year	Average Price Projection (P_{avg}, *\$2001)*
Central AC	Small (<39 kBtu)	1982	1948
Central AC	Large (<39 kBtu)	1982	3072
Room AC	Small (8 kBtu)	1982	698
Room AC	Med (14 kBtu)	1982	963
Room AC	Large (20 kBtu)	1982	1411
Room AC	Small (8 kBtu)	1990	530
Room AC	Med (14 kBtu)	1990	650
Room AC	Large (20 kBtu)	1990	805
Clothes Washer	Standard; 115 v, 2.6 ft^3	1990	300
Refrigerators	Top-mount; Auto-defrost	1989	833
Refrigerators	Top-mount; Auto-defrost	1991/95	764

Accuracy Comparison and Discussion

In evaluating the prediction accuracy of the original constant price assumption in the pre-2011 DOE regulatory impact assessment approach to MEPS (here called the "constant price assumption" projection) as opposed to the average price (P_{avg}) projected from the current MEPS regulatory impact assessment approach, held to the same time period (here called the "PPI-based price trend projection"), we compared these approaches to realized market price (here called "actual price"). Here we provide additional data to support Figure 7 in the main body of this document.

Table 10 summarizes the absolute difference between the actual price, the constant price assumption projection, and the PPI-based price trend prediction, expressed in terms of the percent away from the actual price each projection is. Shaded cells represent the most accurate prediction for each appliance and rulemaking.

Table 10: Comparison of prediction accuracy: constant price vs. price trend projections

Product	Description	Analysis Year	Effective Date	Constant Price Assumption	Avg Price from PPI-Based Price Trend Projection
Central AC*	Small (<39 kBtu)	1982	1988	35%	6%
Central AC*	Large (<39 kBtu)	1982	1988	63%	14%
Room AC	Small (8 kBtu)	1982	1987	52%	28%
Room AC	Med (14 kBtu)	1982	1987	40%	18%
Room AC	Large (20 kBtu)	1982	1987	46%	23%
Room AC	Small (8 kBtu)	1990	1993	7%	3%
Room AC	Med (14 kBtu)	1990	1993	5%	8%
Room AC	Large (20 kBtu)	1990	1993	16%	19%
Clothes Washer	Standard 115 v, 2.6 ft^3	1990	2001	22%	47%
Refrigerators	Top-mount Auto-defrost	1989	1994	15%	4%
Refrigerators	Top-mount Auto-defrost	1991/95	2001	29%	4%

* Note that Dale et al (2009) describes central AC prices as "retail price," and we accordingly apply our price factor estimates to these prices. If these central AC prices in fact include an installation cost, the price factor should only be applied to the retail price, and the accuracy under the price trend method would be somewhat less than our analysis suggests (though still more accurate than under the constant price assumption). All other product prices are described as "retail price" as well, and as none of these products are expected to have substantial installation costs, any error in price definition is less likely to impact our estimates of price trend method accuracy.

Table 11 summarizes the differences in price prediction accuracy in another way, presenting the difference in accuracy between the last two columns in Table 10. Shaded cells represent cases in which the PPI-based price trend projections are more accurate than the constant price assumption projections. Note that the PPI-based price trend projections are often substantially more accurate than the constant price assumption projections. For two of the three product categories in which the constant price assumption is estimated to be more accurate, however, the constant price assumption is only slightly more accurate.[13]

[13] In these two cases, the constant price assumption was already lower than the actual price, so applying a downward sloping price trend would make sense in exacerbating the underestimation.

Table 11. Percentage point difference in accuracy between price projections

Product	Description	Analysis Year	Effective Date	Accuracy of the Avg Price from PPI-Based Price Trend Projection minus the accuracy of the Constant Price Assumption
Central AC	Small (<39 kBtu)	1982	1988	28%
Central AC	Large (<39 kBtu)	1982	1988	49%
Room AC	Small (8 kBtu)	1982	1987	24%
Room AC	Med (14 kBtu)	1982	1987	22%
Room AC	Large (20 kBtu)	1982	1987	23%
Room AC	Small (8 kBtu)	1990	1993	4%
Room AC	Med (14 kBtu)	1990	1993	-3%
Room AC	Large (20 kBtu)	1990	1993	-3%
Clothes Washer	Standard 115 v, 2.6 ft^3	1990	2001	-26%
Refrigerators	Top-mount Auto-defrost	1989	1994	10%
Refrigerators	Top-mount Auto-defrost	1991/95	2001	25%

As the price trend method has only been included in rules published since February 2011 (with effective dates in the range of about 2014 to 2017), it will still be several years before the predictions of the underlying analyses of these rules can be tested against real world costs and prices. However, our application of the PPI-based price trend projection to the older data in Dale, Antinori et al. (2009) suggests that, in most cases, price forecast accuracy would have been improved if today's DOE approach to regulatory impact assessment had been available to analysts in earlier years.