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Progress in Energy Storage Technologies: Models and Methods for Policy Analysis

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Progress in Energy Storage Technologies:
Models and Methods for Policy Analysis

By Schuyler W. Matteson

A Dissertation Submitted in Partial Fulfillment of the
Requirements for the Degree of
Doctorate of Philosophy in Sustainability

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Submitted by Schuyler W. Matteson in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Sustainability and accepted on behalf of the Rochester Institute of Technology by the dissertation committee.

We, the undersigned members of the Faculty of the Rochester Institute of Technology, certify that we have advised and/or supervised the candidate on the work described in this dissertation. We further certify that we have reviewed the dissertation manuscript and approve it in partial fulfillment of the requirements of the degree of Doctor of Philosophy in Sustainability.

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ABSTRACT

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Title: Progress in Energy Storage Technologies: Models and Methods for Policy Analysis

Climate change and other sustainability challenges have led to the development of new technologies that increase energy efficiency and reduce the utilization of finite resources. To promote the adoption of technologies with social benefits, governments often enact policies that provide financial incentives at the point of purchase. In their current form, these subsidies have the potential to increase the diffusion of emerging technologies; however, accounting for technological progress can improve program success while decreasing net public investment.

This research develops novel methods using experience curves for the development of more efficient subsidy policies. By providing case studies in the field of automotive energy storage technologies, this dissertation also applies the methods to show the impacts of incorporating technological progress into energy policies. Specific findings include learning-dependent tapering subsidies for electric vehicles based on the lithium-ion battery experience curve, the effects of residual learning rates in lead-acid batteries on emerging technology cost competitiveness, and a cascading diffusion assessment of plug-in hybrid electric vehicle subsidy programs. Notably, the results show that considering learning rates in policy development can save billions of dollars in public funds, while also lending insight into the decision of whether or not to subsidize a given technology.

Abstract Approval:

Committee Chair: ___________________________________

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I. Introduction

1.1 Background and Rationale

Population growth, aging infrastructure, increased electricity demand and the growth of intermittent renewable energy sources have placed new demands on the electricity grid. A variety of options exist to decrease these demands, including energy efficiency measures, transmission and distribution upgrades, and the adoption of energy storage technologies. Of these options, energy storage is the least utilized due to the relative immaturity of the market, though investment in the development of new energy storage has been increasing rapidly. At the same time, consumers and governments are looking for alternative fuel options for personal transportation. Energy storage in the form of vehicle batteries has been a key component in the growth of the plug-in hybrid electric and all-electric vehicle markets. As a result, the energy storage sector is consistently introducing new technologies for both grid and automotive applications. A recent report predicts that the global market for energy storage for grid use alone could rise from $200 Million in 2012 to over $10 Billion in 2017 (Warshay 2013). However, even with new systems, such as lithium based batteries, flywheels, and compressed air technology, providing a range of potentially valuable services, mature technologies that have achieved lower cost through experience and scale have only recently begun to lose market share to emerging technologies (KEMA 2012).

To bridge the gap in upfront capital cost between emerging technologies and the incumbents, billions of dollars of public funds are spent every year to incentivize the adoption of technologies with perceived public benefits. These subsidy programs are often developed without clear description of methods and information, and may result in a less than optimal allocation of funds. This research intends to use the experience curve as a predictor of technological progress to draw insight into the future costs of emerging energy storage technologies to help create lower cost and higher impact subsidy policies.

The experience curve and its variants are often used for energy policy analysis (*International Energy Agency* 2000; Junginger et al. 2005; Neij et al. 2003), and allow users to quantify and forecast cost reductions in a technology as cumulative production increases. Tsuchiya (1989) is among the first to utilize experience curves to quantify the total investment needed to bring a technology, in his case photovoltaics, to price parity. Herron and Williams (2013) analyze how differences in willingness to pay among different consumers influences the subsidy required to bridge the gap between current and target costs. Experience curves have also been used to forecast technological growth in many energy technologies (Harmon 2000; Weiss et al. 2010).

The empirical experience curve gives a statistically robust fit over a range of costs and production for variety of energy technologies (Neij et al. 2003), including photovoltaic (Harmon 2000; van der Zwaan and Rabl 2004), wind (Junginger et al. 2005), and coal (Yeh and Rubin 2007). Figure 1 shows the well-known derivation of the photovoltaic experience curve, which uses historical cost and production data to determine the percentage decrease in module cost for each doubling of cumulative production. Further applications and review of experience curves is presented in Anzanello and Fogliatto (2011). There is also a stream of literature which seeks to develop multi-factor experience curves that distinguish factors such as learning by doing, learning by searching, economies of scales and material costs (Kobos et al. 2006).

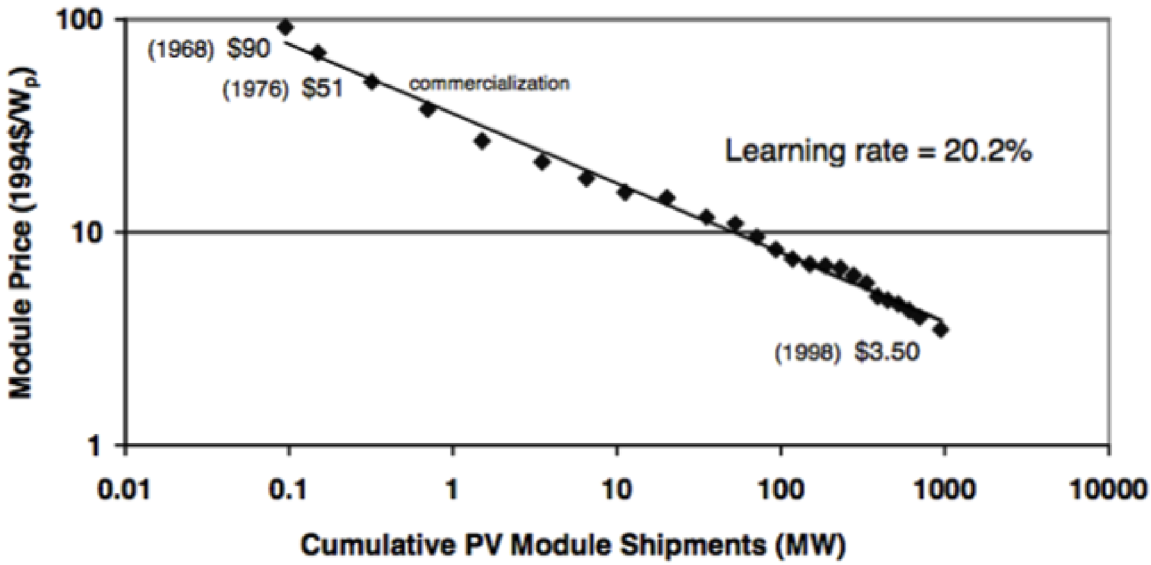


Figure I. The experience curve of photovoltaic modules (Harmon 2000)

There is a gap in the literature, with a limited amount of technological progress studies, including experience curves and learning rate information for energy storage technologies. There is also limited application of this information to policy analysis. Some studies assess the progress of batteries through the lens of technical performance characteristics. For example, Gerssen-Gondelach and Faaij (2012) project likely scenarios for lithium-ion battery performance traits over various timelines to determine whether the batteries may be able to reach certain energy, emissions, and cost targets. Mayer et al. (2012) address technological progress modeling by forecasting the cost of proton exchange membrane fuel cells and lithium-ion batteries to 2020 using an augmented two-factor experience curve. However, the methods result in a scenario analysis of the experience curve model, in order to determine input criteria for meeting various 2020 cost targets.

This project fills the gap by providing case studies for constructing the experience curves of three separate energy storage technologies including lithium-ion batteries, lead-acid batteries, and plug-in hybrid electric vehicles. The experience curves are developed utilizing a traditional single factor experience curve, which is augmented based on the technology's material inputs and costs and is utilized for policy and market analysis.

There are also three new methods developed, one in each section, to supplement the literature on policy analysis for energy technologies. Each method utilizes information derived from the experience curves to show how the incorporation of technological progress models improves policy development and assessment. The first method is for developing cost-effective learning-dependent tapering subsidies and is outlined to show the benefits of using technological learning analysis in subsidy program development. Second, new residual experience curve methodologies are used to assess how learning rates in incumbent technologies affect policies and markets for emerging technologies. Finally, market curves constructed using various resolution levels are combined with experience curves to determine how diffusion patterns are affected in fractional markets.

1.2 Research Objectives

This research has been completed to provide additional resources to policymakers and new information and methodologies to researchers. New case study information is provided regarding the historical development of energy storage technologies, and is in the form of newly developed experience curves and learning rates for three separate energy storage technologies, including lithium-ion batteries, lead-acid batteries, and plug-in hybrid electric vehicles. This contribution expands the knowledge base of sustainable energy research by providing additional resources to those studying technological progress.

The second area of contribution is methodological: in each of the three chapters, a new method is developed to aid in the assessment of technological learning and provide guidance to those interested in the adoption of emerging technology. These new methods result in policy implications and recommendations in the specific cases presented, and also allow for a wide range of applications to other energy technologies and markets.

The specific methods developed include:

- The creation of learning-dependent tapering subsidies based on changes in the distance between the experience curve and a cost target, using lithium-ion batteries as a case study,
- The development of a residual experience curve – experience curve minus material costs – and learning rates in lead-acid batteries and the application of the results in a gap-to-parity analysis (the distance of a technology to price parity) of lithium batteries, and
- The construction of a person-level market curve for a cascading diffusion analysis of plug-in hybrid electric vehicles.

With better information, researchers and policymakers can create more efficient policies to enhance the adoption and diffusion of key sustainability technologies. Higher economic efficiency in the promotion of these technologies, such as electrified transportation and energy storage systems, benefits society by providing improved technical performance and decreased environmental impacts, which satisfies the three pillars of sustainability.

1.3 Dissertation Outline

The case study and method contributions described above are explained in Chapters II, III, and IV respectively. An outline of the dissertation and a summary of each chapter are provided below:

Chapter II: Governments subsidize diffusion of a variety of energy technologies believed to provide social benefits. These subsidies are often based on the idea that stimulating learning and industry development will lower costs to make the technology competitive, after which point the subsidy can be removed. Two questions related to the design of subsidy programs are investigated. One question is how net public investment changes with the time interval over which subsidies are reduced, i.e. semi-annually, annually, etc. Governments prefer to reduce subsidies more often to lower public costs, producers prefer longer time periods for a more stable investment environment. The second question addressed is uncertainty in learning rates. Learning rates describe the fractional cost reduction per doubling of cumulative production; slower learning implies more government investment is needed to reach a cost target. These questions are analyzed via a case study of subsidizing electric vehicles (EV) in the United States. Given the importance of lithium battery cost in the price of an EV, historical data is gathered to build an experience curve that describes cost reductions for lithium-ion vehicle batteries as a function of cumulative production. Our model assumes vehicle batteries experience the same learning as consumer electronics, yielding a learning rate of 22%. Using learning rates ranging from 9.5-22%, the public subsidy needed to reach a battery cost target of $300/kWh battery in ten years is estimated. For a 9.5% learning rate, semi-annual, annual and biannual tapering costs a total 24, 27, and 34 billion USD respectively. For 22% learning, semi-annual, annual and biannual tapering costs a total 2.1, 2.3, and 2.6 billion USD respectively.

While the tapering does affect program cost, uncertainty in learning rate is the largest source of variability in program cost, increasing the importance of realistic ranges for learning rates when planning electric vehicle and other technology subsidies.

Chapter III: The low price of lead-acid, the most popular battery, is often used in setting cost targets for emerging energy storage technologies. Future cost reductions in lead acid batteries could increase the investment and time scales needed for emerging storage technologies to reach cost-parity. To characterize cost reductions, this chapter develops the first documented experience curves for lead-acid batteries. Results of regression to a standard experience curve using 1985-2012 data yield a poor fit, with R^2 values of 0.17 for small batteries and 0.05 for larger systems. To address this problem, battery costs are separated into material costs (of which lead is the largest component) and residual costs, and find experience curves for residual costs. Running time averages are also used to address market volatility in material costs. These two modifications increase R^2 to 0.78 and 0.74 for small and large systems respectively. The learning rate for residual costs is found to be around 20%, a discovery with policy implications. Neglecting to consider cost reductions in lead-acid batteries could result in failure of energy storage start-ups and public policy programs. Generalizing this result, learning in incumbent technologies must be understood to properly assess the potential of emerging technologies.

Chapter IV: The social benefit of energy technology subsidies is typically underestimated when considering only the costs and benefits per item directly subsidized. This approach misses the motivation underlying many subsidies: increased production drives technological progress and reduces cost. When the cost of a subsidy is calculated including the "free" diffusion that occurs after the technology becomes economically competitive, the social benefits of the subsidy are markedly greater. Subsidies for Plug-in Hybrid Electric Vehicles (PHEV) in the U.S are examined, showing that accounting for technological progress and eventual market activation reduces the subsidy cost per vehicle by over 90%, suggesting that the current $7,500 per vehicle PHEV subsidy is in the public interest. The modeling framework shows, more generally, that assessing technological progress is critical to understand the benefits of a subsidy policy.

Chapter V: This chapter summarizes the key results of this dissertation regarding experience curves for energy storage technologies and the potential to improve future policies.

II. Learning-Dependent Subsidies for Lithium-Ion Electric Vehicle Batteries

2.1 Introduction

Electric vehicles (EV) are thought to provide a variety of benefits to society, including decreased emissions, improved environmental performance in regions with clean grid electricity, and have recently shown safety improvements over internal combustion vehicles due to increased crumple zones and low centers of gravity (Inside EVs 2013). Due to these potential benefits, federal and state governments in many countries offer subsidies and/or tax credits toward the purchase of EVs. In the United States, for example, the federal incentive is an income tax deduction of up to $7,500 depending on the battery capacity of the vehicle and is set to end after the first 200,000 EVs purchased (Department of Energy 2013).

EV subsidies are an example of broader government efforts to promote the development of energy technologies viewed as socially desirable, such as photovoltaic modules (Dincer 2011), and fuel cells (Brown et al. 2007). In general, a diffusion subsidy is set up to support a technology at a specified level over a fixed time period (Kimura and Suzuki 2006) or target production level (Internal Revenue Service 2013). At the expiration date and/or production level, a decision is made to cease or decrease the subsidy. A recent, more innovative system in Europe sets an explicit schedule for annual subsidy decreases (degression) for feed-in-tariffs (FIT) for renewable energy (del Rio 2012; Munoz et al. 2007; Wand and Leuthold 2011). The idea behind degression is that government support should decrease as costs fall due to industry development, e.g. (Kimura and Suzuki 2006; del Rio 2012)

There are important questions as to how to best design subsidy policies. A pervasive challenge is how to explicitly embed technological progress into planning reductions of the subsidy over time (Wand and Leuthold 2011; Herron and Williams 2013). Ideally, a diffusion subsidy stimulates the industry to reduce cost to the point that the subsidy is no longer needed. The central idea is to fix the subsidy rate as the difference between the technology and the average consumer's willingness to pay. Once the technology reaches the average willingness to pay, price parity has been achieved and the subsidy is removed.

A variety of prior work has explored relationships between technological progress and subsidy policies. The experience curve, a empirically observed power law decline of cost as a function of cumulative production, is often used to forecast future costs (International Energy Agency 2000; Junginger et al. 2005; Neij et al. 2003). Tsuchiya (1989) pioneered the use of experience curves to quantify the total investment needed to bring a technology to price parity, in this case, photovoltaic modules. Wand and Leuthold (2011) embed learning rates into a larger model estimating the public benefits and costs of the FIT of PV in Germany. Herron and Williams (2013) analyze how differences in willingness to pay among different consumers influences the subsidy required to bridge the gap between current and target cost.

A critical design component of a subsidy is how it is tapered, i.e. how often and by how much it is reduced. There is an important tension to balance in the frequency of tapering: governments prefer to reduce the subsidy more often in response to cost reductions in order to lower public costs. Producers on the other hand prefer longer-term subsidy commitments to justify capital investments. There are also administrative considerations, e.g. reducing a subsidy every week would not be practical to implement.

Two open questions with respect to subsidy design are explored. The first is how public subsidy investments change as a function of the time interval over which the subsidy is tapered, e.g. annually, biannually or otherwise. European FIT policies, for example, assume an annual reduction, but it is worth examining the implications of other choices. The second question is how variability in learning rates effect the public investment required to reach cost parity. Prior analyses of subsidy-induced progress assume a single learning rate value (Wand and Leuthold 2011; Tsuchiya 1989). However, there is substantial variability in learning rates (Electric Power Research Institute 2013), and lower learning could substantially increase the public investment required to reach price parity. The German FIT policy goes the furthest to account for variability in expected learning by allowing optional year-end adjustments of plus or minus 1%, according to observed cost reductions (Klein et al. 2010; Ragwitz and Huber 2005). It is important, however, to explicitly analyze the variability in public investments as a function of uncertain learning rates at the outset. This will inform the degree of flexibility to build into the subsidy and also government willingness to invest if cost reductions are lower than baseline expectations. A model is therefore constructed to estimate the net government subsidy required to reach price parity as a function of how often the subsidy is reduced for various set learning rates.

These questions are analyzed via a case study of the subsidy of electric vehicles in the United States. The case study has its own merit; in particular it produces the first publicly available experience curve for lithium batteries. While the International Energy Agency reports a value for EV battery learning rates (International Energy Agency 2013), the underlying data and analysis are not publicly available. The main challenge in building an experience curve is lack of publicly available data on price/cost and production. An experience curve using the assumption that learning rates for vehicle lithium batteries will be similar to their consumer electronics counterparts, for which historical data are available.

This choice will increase uncertainty in the results, though the methods for constructing the curve in this analysis can be utilized again when future data become available. Furthermore, larger lithium-ion batteries that are used in electric vehicles are most often simply a collection of smaller cells, like those in consumer electronics, connected in a circuit, and share materials, chemistry, and energy characteristics (Andrea 2010). For example, 6,000 – 8,000 of the most common type of small cell lithium-ion battery, the 18650, are combined to form the new Tesla Model S battery pack (Fisher 2013; Mayer et al. 2012). There are additional components in this case, such as a control system and wiring, though for this analysis we do not assess learning in these components, and choose to represent lithium-ion electric vehicle battery learning as analog to learning in smaller lithium-ion batteries.

In recent years, lithium-ion batteries have grown in popularity and applications, resulting in active research and development, particularly for transportation. Much of the published research centers around reducing the costs of these batteries (Anderson 2009; Axsen et al. 2008; Gaines and Cuenca 2000; Cready et al. 2003; Kalhammer et al. 2007; Takashita 2007; Lowe et al. 2010; Barnett 2009). Another stream of research examines the resource and environmental implications of battery use (Dunn et al. 2012; Gaines et al. 2010; Goonan 2012; Notter et al. 2010; Wilburn 2008; Zackrisson et al. 2010). Research, development and industrialization has led to improved battery performance and reduced cost.

Over the past few decades, lithium-ion batteries have been most commonly used to power small electronic devices, such as laptop computers and mobile phones. Due to their high specific energy, lithium ion batteries are becoming the dominant technology for Electric Vehicles (EVs). Currently though, they are an expensive choice compared to gasoline in internal combustion engines, stemming from a lack of economies of scale and high materials costs. In many cases, the EV battery accounts for around 50% of the total cost of the vehicle (International Energy Agency 2013). High battery costs imply EVs are not economically profitable for most consumers, presenting a substantial barrier to adoption. However, battery costs continue to fall. The rapidity and extent of cost reductions in lithium-ion batteries is a critical driver of the affordability of EVs in the near term.

While impacts from the life cycle of batteries need assessment and management (Notter et al. 2010), questions regarding the current and future environmental benefits of electric vehicles will not be addressed. In addition, it has been argued that the operation phase of an electric vehicle is only as clean as its electricity supply (Michalek et al. 2011), though other studies suggest pollutants will be reduced regardless of the power supply due to improvements in energy efficiency by switching away from internal combustion engines (Electric Power Research Institute and National Resources Defense Council 2007; Massachusetts Institute of Technology 2010). Carbon and criteria air pollutant emissions associated with EVs are expected to reduce along with increased electricity production from renewable sources. The co-evolution of the electricity grid and future demand from EVs is, however, a complicated matter.

2.2 Methodology

2.2.1 Experience Curve

The experience curve is a mainstay of retrospective forecasting for energy technologies. Developed first to describe cost reductions in aircraft manufacturing (Wright 1936), the experience curve is an empirically observed power law decay of some characteristic of industrial processes and cumulative experience implementing that process (Teplitz 1991; Yelle 1979). In the energy domain, the experience curve takes the form:

$$C(P) = C_0(P/P_0)^{-\alpha} \quad (1)$$

where P is a measure of cumulative adoption of the technology (e.g., the total kilowatt-hour capacity of batteries produced), C is the price per energy unit (e.g., $/$W_p$ or $/kWh), C_0 and P_0 are initial cost and production values, α is a (positive) empirical constant, known as the learning coefficient. The fractional reduction in cost for every doubling of production is known as the Learning Rate (LR) and is given by

$$LR = 1 - 2^{a} \quad (2)$$

Equation (1) gives a statistically robust fit over a surprising range of costs and production for variety of energy technologies (Neij et al. 2003), including photovoltaic (Harmon 2000; van der Zwaan and Rabl 2004), wind (Junginger et al. 2005), circuitry (Moore 1965), and coal (Yeh and Rubin 2007). Experience curves have been used to forecast progress for a variety of energy technologies (Harmon 2000; Weiss et al. 2010). There is also a stream of literature to develop multi-factor experience curves that distinguish factors such as learning by doing, learning by searching, economies of scales and material costs (Kobos et al. 2006; Yu et al. 2011). In this chapter, a single factor experience curve is used, focusing on how to utilize it for subsidy policy analysis. Future analyses could include potential spillover effects from other types of battery production; such as additional types of consumer electronics or batteries manufactured for use in uninterruptable power supply systems.

Note that this analysis utilizes experience curves rather than learning curves. Conceptually, the terms are very similar, however they are technically different in that experience curves refer to the reduction in production costs (labor, process, etc.) with every doubling of cumulative production, whereas learning curves refer only to the reduction in direct labor input (hours worked, etc.) required to complete a task (produce one battery).

At varying learning rates, lithium-ion batteries will require different quantities of cumulative production to reach cost targets, following the relationship that higher learning rates require less production to meet the per kWh cost goal. These production totals are calculated using the equation

$$P_{C_t} = P_0 \times \left(\frac{C_t}{C_0}\right)^{\left(\frac{1}{a}\right)} \tag{3}$$

where P_{Ct} is cumulative production needed to meet the cost target, P_0 is cumulative production in the initial year, C_t is the target cost of the technology, and C_0 is the cost of the technology in the initial year. Note that equation 3 is a reorganization of equation 1. This allows us to input the empirically determined learning rate to solve for the cumulative production.

The cumulative production targets vary substantially, meaning that at similar annual production rates, scenarios operating at low learning rates will take much longer to reach cost goals than those at higher learning rates. Analogously, at different learning rates, cost reductions occur at different rates. At a given level of cumulative production, the learning rate will determine the number of units needing to be produced to reach the cost target.

2.2.2 Subsidy costs

Given that the primary goal of a subsidy is to bring the technology to price parity, the learning-dependent investment formula can used to determine the subsidy (S) needed for a given level of production (P): the difference between the experience curve cost and a target cost (C_t) that represents price parity with some alternative:

$$S = C_0 \times \left(\frac{P_0}{P}\right)^{(a)} - C_t \tag{4}$$

As units are produced and cumulative production increases, the subsidy decreases until the technology reaches price parity, at which point government support can be withdrawn. Equation 4 allows us to calculate the instantaneous subsidy, the subsidy required at any given point of the experience curve.

Equation 4 can be integrated to calculate the total cost of a subsidy plan, representing a scenario in which the subsidy is reduced infinitesimally for each incremental increase in production:

$$Min\{Subsidy(P)\} = \int_{P_0}^{P} \left(C_0 \left(\frac{P}{P_0}\right)^{\alpha} - C_t\right) dP \tag{5}$$

Continuous decrease of the subsidy is infeasible from an administrative standpoint, in practice the subsidy needs to be reduced over discrete intervals of increases in production. Figure 1 illustrates different tapering schedules and how the schedules affect total public investment. Instead of an integral of the experience curve, the total investment in a tapered subsidy is the sum of rectangular areas with each height as the experience curve cost during an interval, and the width is the difference in production over the interval. The red line in figure 1 represents a flat subsidy that remains constant over the life of the program. The green and blue lines are tapered more frequently, while a subsidy plan that follows the black curve is tapered with each unit of production. The black line represents the minimum subsidy policy, calculated with equation 5. The area under each separate colored line represents the total cost of the subsidy plan. Clearly, the red line subsidy plan results in the highest total cost, while tapering more frequently reduces the total cost of the plan.

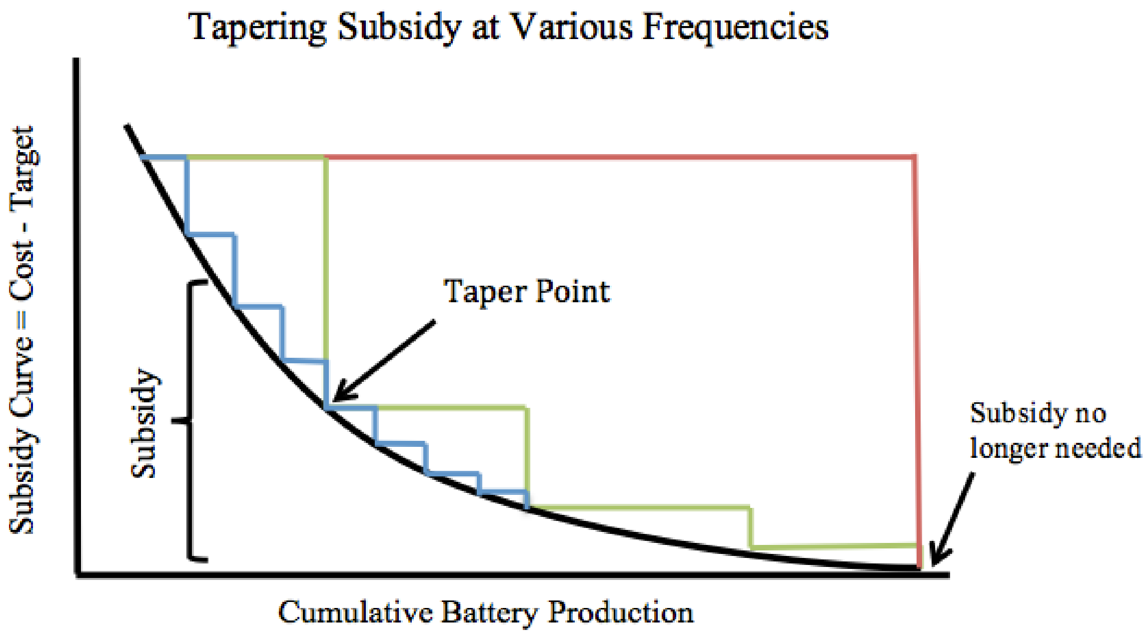


Figure 1. Comparison of subsidy levels (red, green, blue) for different tapering schedules. The area under each separate line is the total public investment for the subsidy plan.

2.2.3 Cost Target

It is common in policy analysis to compare the cost of an evolving technology to some cost target or price parity, typically chosen as static in time (International Energy Agency 2013; Howell 2012; Tsuchiya 1989; Wand and Leuthold 2011). While it is certainly worth considering dynamic and heterogeneous targets, to bound the scope of this work the following practice is used. For EVs, the International Energy Agency and the Department of Energy use a cost target of \$300/kWh for vehicle batteries (Howell 2012; International Energy Agency 2013). While this number is not explained, it is found to correspond to the net present value of electric and conventional vehicles becoming equivalent for plausible values of input parameters (e.g. vehicle lifespan of 10 years, 10,000 miles driven annually, \$3.50/gallon gasoline price, discount rate of 5%). Lithium-ion batteries for vehicles reportedly cost \$600/kWh at the end of 2012 (International Energy Agency 2013).

In reality this target is a moving one, because gasoline and electricity prices vary over time. However, gas prices are expected to increase in the future rather than decrease, and therefore this target represents an upper bound on the total subsidy program costs for EVs, since any increase in gas price will raise the target line, decreasing the distance between the technology cost and the target.

Chapters III and IV incorporate alternative methods for determining the cost target of a given technology, in order to account for potential variability or heterogeneity in the parity price. Whereas the current chapter assesses a constant target price, chapter III treats price parity for emerging technologies as the cost of the incumbent technology, which more than likely is not constant. In that case, the parity price is often a moving target, corresponding to cost reductions in the incumbent proportional to the incumbent's learning rate. Chapter IV takes the price parity discussion a step farther, treating the target cost as a heterogeneous value that varies by consumer. The cost target is thus different for each consumer, and is represented by the individual's economic willingness to pay for the emerging technology relative to the incumbent.

Figures A1 and A2 in Section 6.1 of the Appendix show how reducing the cost target would affect the total cumulative production required to meet the goal. A small decrease in the price parity target, whether due to technological learning in an incumbent technology or an increase in the emerging technology's material costs, can drastically affect the cumulative production requirement, thereby increasing the total cost of the subsidy program. Depending on how large the gap to price parity becomes, the subsidy program cost may exceed social or environmental, causing policymakers to halt incentives for the technology.

2.2.4 Justifying Zero Long-Term Cost

In equation (1) the limit as cumulative production goes to infinity is zero cost. Obviously, no technology has zero cost; the implicit assumption is that long-term cost is too small to influence the variable region over which the equation is being used. While there can arise practical obstacles to progress in cost reduction that are difficult or even impossible to predict, it is possible to estimate an asymptotic cost based on material prices in the thermodynamic limit. Estimating this cost and comparing it to the cost target is part of the process of using equation (1) for the assessment of energy technologies. Due to the high potential for efficiency improvements in lithium batteries (Srinivasan 2008) the asymptotic cost per kWh of the technology is very small. Using current experimentally determined material composition data (Wang et al. 2013), applying thermodynamic efficiency limits (R. A. Huggins 2010), and utilizing current material cost data (Infomine 2013), the asymptotic cost is estimated to vary between $3 and $11 per kWh, or around 1-2% of current costs. Since asymptotic cost is significantly less than the target cost and it would not noticeably affect the results, the asymptotic cost is neglected hereafter.

2.2.5 National versus International Experience Curves and Subsidy Policies

Many technologies, including electric vehicles, are produced by multi-national companies and have global markets. The experience curve for many components of a technology should thus apply to global prices and global cumulative production. This section focuses on a national analysis (the United States) based on the following rationale: While there is potential for international coordination (Herron and Williams 2013), subsidy policies are currently a domestic affair. Without doubt, a nation considering a subsidy policy will see the effects of lower prices due to adoption in other nations. However, a national policy ought to realize its goals regardless of actions taken outside its jurisdiction.

This is not always optimal or even feasible, but analyzing a purely national policy is an appropriate starting point, particularly since the US represents nearly 40% of the global EV stock (International Energy Agency 2013). If the national policy is deemed too expensive or otherwise ineffective, analysis can be expanded to include actions by other nations. While learning in lithium batteries for consumer electronics could also contribute to a reduction in the price of electric vehicles, this consideration is neglected via reasoning analogous to the above. It is important to understand the potential of an EV subsidy aside from possible spillovers from other sectors.

2.3 Results and Discussion

2.3.1 Experience Curve

It is preferable to use cost data to develop the experience curve, equation (1), but here, as in many other cases, only price data is available. Historical pricing for lithium-ion batteries in consumer electronics over the interval 1993-2005 was taken from (Brodd; Takashita 2007). These prices are converted to real 2005 dollars using annual national inflation rates for the United States (Inflation Calculator 2013). Annual production data, on a per kWh basis, are found for lithium-ion batteries in consumer electronics (Battery University 2013). This is converted to cumulative production so that the adjusted data, shown in Table 1, is suitable for fitting an experience curve.

Year	Price ($/kWh)	Cumulative Production (GWh)
1993	2522	0.12
1994	2111	0.32
1995	2063	0.94
1996	1496	2.1
1997	1146	3.6
1998	712	6.2
1999	615	10
2000	507	16
2001	422	23
2002	422	33
2003	398	44
2004	374	61
2005	338	78

Table 1. Historical Price and Production Data for lithium-ion batteries (in 2005 US$) (Brodd; Takashita 2007; Battery University 2013)

Fitting this data to Equation (1), the historical learning rate for lithium-ion batteries is found to be 22% for the time period between 1993 and 2005. The curve and data are plotted together in Figure 2, and the resulting r-squared value for this statistical fit is 0.955. It is important to note that during this time period, lithium-ion batteries were used primarily for small portable electronics.

Throughout this paper the initial cost of lithium-ion batteries is taken to be $600/kWh (Howell 2012) and the initial production level is 2.3 million kWh annually in 2012 (International Energy Agency 2013). In a recent publication, the IEA reports having calculated a learning rate of 9.5% for EV batteries (International Energy Agency 2013). Data supporting the calculation of these learning rates is not provided however, and it is not entirely clear what types of batteries or price/cost measures are being used. Regardless, there is clearly significant uncertainty in future learning rates and to account for this, a range of learning rates are considered, including the range between the empirically derived value and the IEA value.

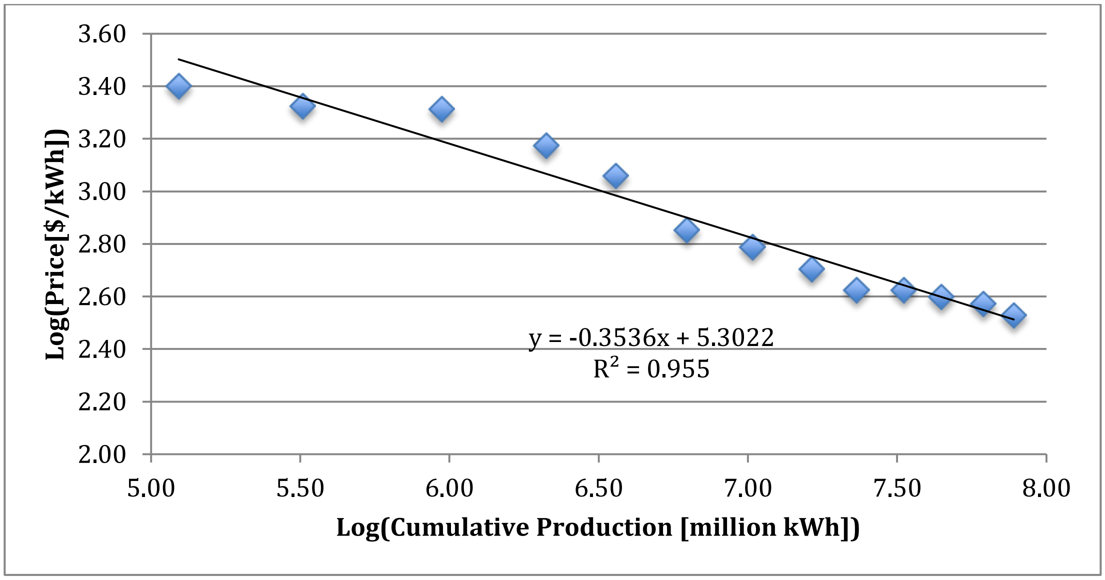


Figure 2. Experience Curve for Lithium-ion Batteries 1993-2005.

The experience curve used is thus

$$C(P) = 600\,\frac{\$}{kWh}\left[\frac{P}{2.3e6}\right]^{-log_2(1-LR)},$$

Where P is measured in kWh. The existing range of learning rates between 9.5 and 22% is examined. Some results are shown as a function of this range, and others using the IEA (9.5%) scenario.

2.3.2 Subsidy Analysis

The learning space, consisting of learning rates between 5% and 25%, is used in equation 3 to calculate the cumulative production needed to reach the cost target, and the results are shown in figure 3. With a 22% learning rate, lithium-ion batteries will reach a cost target of $300/kWh after 26 million kWh of cumulative production, but at the IEA rate of

9.5%, 425 million kWh of additional battery capacity would be required to reach the same target. The total production of capacity required spans orders of magnitude, highlighting the importance of the value of the learning rate.

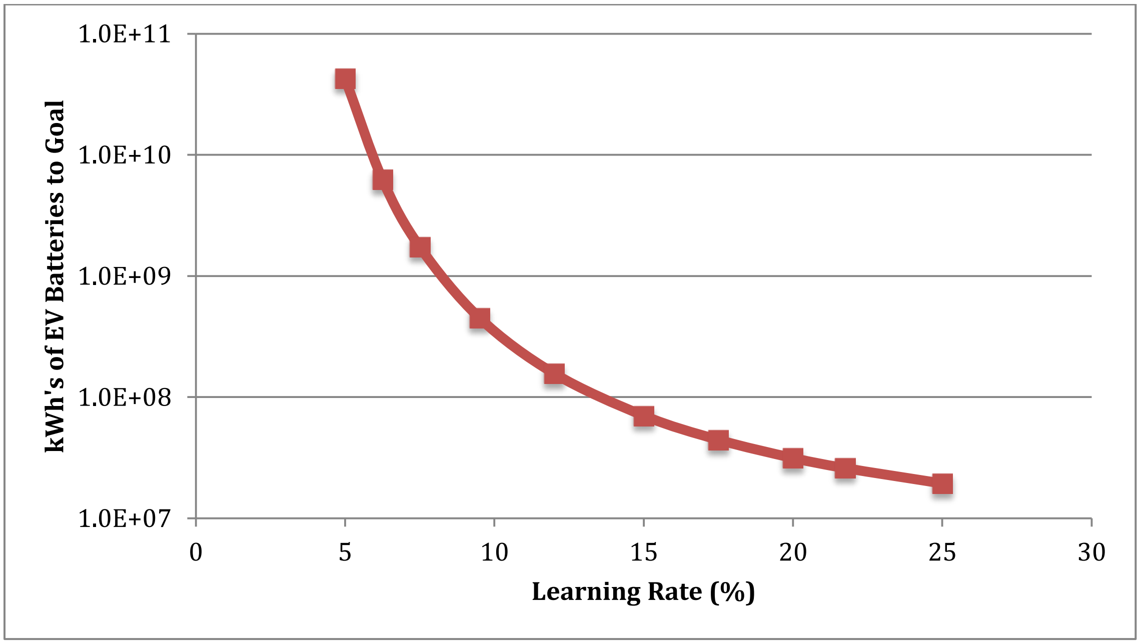


Figure 3. Cumulative production of lithium-ion batteries needed to reach cost target of $300/kWh as a function of learning rate

Shown in figure 4, results for the total cost of a continuous decreasing subsidy range from $2 – $87 billion as a function of learning rate, while the total cost of an annually tapered subsidy range from $1 – $18 billion. This is because at higher learning rates, much less cumulative production is required to reach the cost target, as shown by figure 3. As the cumulative production needed to reach the goal increases, both total public investment and the required annual market growth rate increase.

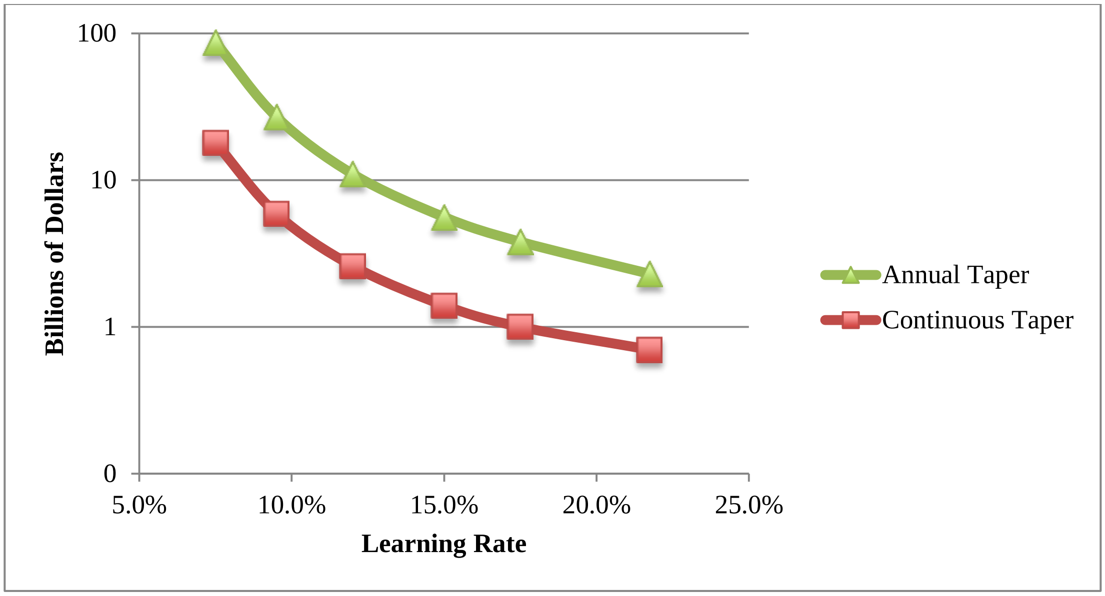


Figure 4. Total subsidy cost as a function of learning rate and tapering interval

An important aspect of figure 4 is how tapering affects total cost at each learning rate. Tapering less frequently increases total cost, shifting the curve up. This phenomenon is shown by the total program costs for different learning rates and taper schedules in Table 2, and will be discussed further in the following sections. Figure A3 in Section 6.1 of the Appendix expands on this idea by illustrating the reductions in subsidy level as cumulative production increases at various learning rates.

	7.5%	**9.5%**	**12.0%**	**15.0%**	**17.5%**	**21.7%**
Semi-Annual	75	24	10	5.1	3.5	2.1
Annual	87	27	11	5.6	3.8	2.3
Bi-annual	115	34	14	6.7	4.4	2.6

Table 2. Total cost of an electric vehicle subsidy program, in billions of USD, for select learning rates and taper schedules.

2.3.3 EV market growth rates and learning

The experience curve does not contain a time component. Ramping up manufacturing and building consumer markets both have rate limitations, thus is important to consider how quickly the EV industry would need to grow in order to achieve the cost target. Three time frames are considered: 10, 15 and 20-year goals. These time frames are representative of practical goals for the lithium-ion battery market, but are longer compared to aggressive programs such as the recent “EV Everywhere Grand Challenge” in the United States, which sets a goal of five years or less (Department of Energy 2011), and the goal of cost parity by 2020 set forth in the recent “Global EV Outlook” (International Energy Agency 2013). Figure 5 shows the relationship between learning rate and the annual growth rate needed to meet different timeline goals. Due to the exponential relationship, marginal increases in the learning rate lead to drastic changes in necessary growth rates. While it is difficult to alter a technology’s learning rate, figure 5 does show that it is important to have a grasp on the learning rate in order to set reasonable market goals.

At the historical 22% learning rate, battery price falls rapidly with production and only 26 million kWh of lithium-ion battery capacity must be produced worldwide to reach a $300/kWh cost target. This is equivalent to about 1.3 million EVs with an average battery size of 20 kWh. At an annual growth rate of 22%, this would be achieved in ten years. To put this in perspective, the IEA reports that in 2012, the EV market grew by over 160% (International Energy Agency 2013). While this rate is unlikely to continue for a decade, growth rates in excess of those needed in the 22% learning rate scenario are possible.

With the slightly more favorable IEA learning rate of 9.5% a total of about 450 million kWh or around 23 million lithium-ion electric vehicle batteries must be produced to reach the cost target. A growth rate of 62% is necessary to meet the target in ten years. Additionally, if all of this purchasing occurred within the United States, EVs would represent about ten percent of the country's total vehicle fleet by 2022 (Department of Transportation 2013).

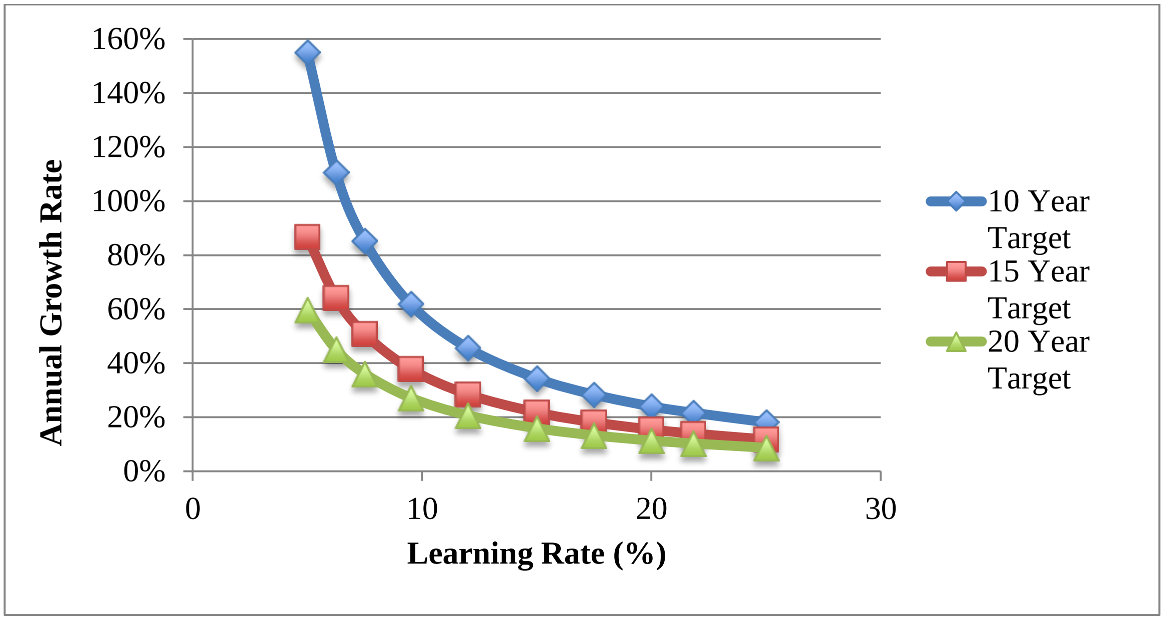


Figure 5. Annual growth in lithium-ion battery production necessary to meet cost goal in target number of years at various learning rates, and annual tapering

2.3.4 Discrete Subsidy Tapering

Figure 4 shows the total cost for a continuously decreasing subsidy. As mentioned earlier, in practice subsidies must be tapered in discrete steps. Regular intervals (e.g. annual, biannual) are presumed to be preferable to provide stability for producers and consumers, although different tapering schedules would affect total subsidy cost. An interval subsidy works as follows. For each learning rate, setting a 10-year target determines required growth rates to meet the target, shown in Figure 5. After a given time interval, the subsidy is reduced to meet the cost reduction via the experience curve, as shown in Figure 1. The areas of each rectangle are added to obtain total subsidy cost until the target is met. Figure 5 shows the total subsidy cost for different tapering schedules. Figure 6 shows the annual and cumulative budget for a subsidy policy with a resolution of one year. The total cost of the plan amounts to $27 billion over the course of ten years.

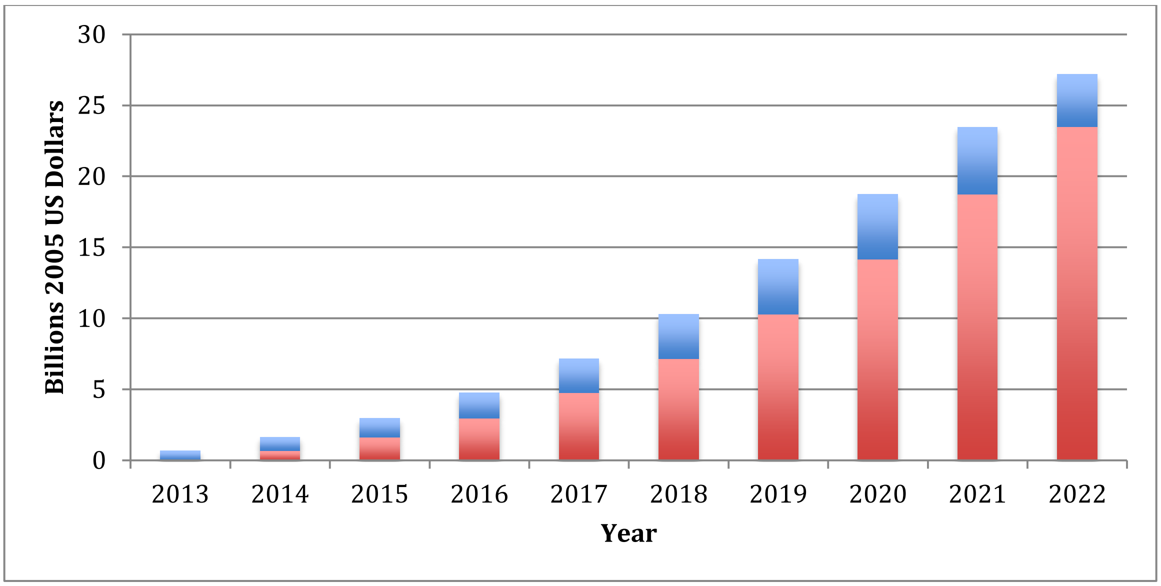


Figure 6. Annual (blue) and Cumulative (red) budget of annually tapered subsidy – 9.5% learning rate, 10 year target to reach $300/kWh cost, 62% EV annual market growth

An important aspect of this plan is the annual budget for the subsidy. While the subsidy per kWh for lithium-ion batteries decreases each year as shown in Table 3, the annual budget for the plan increases every year except the final year of the plan (as shown by the blue segment of the bars in figure 6). This is due to the exponential growth in the production of the batteries, which is a constant 62% growth in annual production per year. The amount of batteries produced increases by a greater magnitude each year under these conditions, gradually increasing the annual budget for subsidies until the final year. Figures A5–A7 in Section 6.1 of the Appendix show how annual and cumulative budget can be increased or decreased by altering learning rates and program timelines.

Year	Subsidy/kWh
2013	**$300**
2014	**$260**
2015	**$222**
2016	**$187**
2017	**$155**
2018	**$124**
2019	**$96**
2020	**$69**
2021	**$45**
2022	**$22**

Table 3. Annual subsidy per kWh for lithium-ion batteries at 9.5% LR and 62% market growth

In the first year of the program, 2013, the current price of lithium-ion batteries is \$600/kWh and the target price is \$300/kWh, therefore the subsidy needed per kWh is \$300. Mathematically, due to the continuous nature of the learning rate formula, the technology learns with each kWh of production, which results in a marginal decrease in cost. It follows then that as the cost decreases, the necessary subsidy decreases as well. However, in this plan the subsidy is re-evaluated only at the beginning of each year, not after each kWh, which essentially results in the government overpaying for all but the first kWh of each year.

The frequency of subsidy tapering is important. If the subsidy is more frequently tapered the total cost of the subsidy plan will decrease, as shown in Figure 4. To more clearly demonstrate variance in the total cost of the subsidy plan as function of interval, Figure 7 shows total subsidy for bi-annually, annually, semi-annually, and quarterly tapering with a learning rate of 9.5%. The growth rate of the EV market is held constant for all time periods to aid in the comparison of the various tapering schedules.

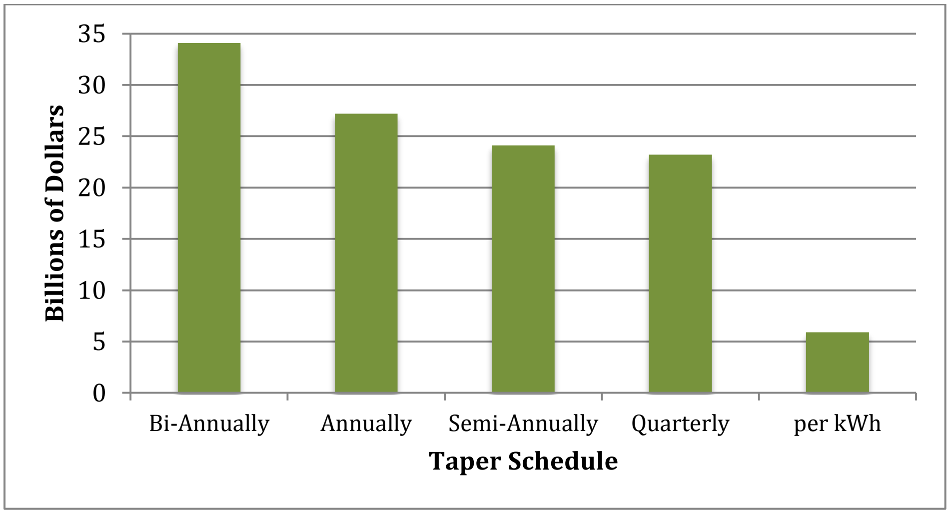


Figure 7. The effect of tapering frequency on total subsidy program cost: learning rate = 9.5%

The calculations show that tapering the subsidy for lithium-ion batteries quarterly as opposed to annually saves $4 billion, or 15% of the total project budget. The cost savings are even greater when compared to flat subsidy programs, in which the same quantity is paid to the consumer over the life of the subsidy. For example, if the subsidy was set to the initial rate, $300/kWh, and maintained at that level for the life of the program, the total cost would amount to $134 billion, four times greater than the annually tapered subsidy, which emphasizes the importance of adjusting subsidy levels.

Figure A8 in Section 6.1 of the Appendix shows how the percentage of the total investment provided by the government varies by tapering schedule. The results show that tapering more frequently not only saves on total program costs, but also reduces the technology's dependence on public funds. This allows the government to provide a smaller percentage of the total investment required to drive adoption of a technology; in this case, electric vehicles.

2.3.5 Policy Discussion

The results indicate that, when tapering annually, the total cost of a lithium-ion battery subsidy is in the range of $2-27 billion for learning rates from 9.5-22%. Setting aside the robustness of this range for the time being, the policy implications of this result are discussed next. To first recap the current U.S. subsidy since 2009, consumers purchasing an electric vehicle are entitled up to a $7,500 tax deduction (Internal Revenue Service 2013). Our results suggest that this current subsidy level of $7,500 per EV roughly matches the gap between current EV prices and the government cost target. Adoption of EVs, partly due to this subsidy, has increased rapidly in recent years, with the number of EVs purchased more than doubling each of the past three years. While renewal is possible, the current subsidy is phased out after three production increments of 200,000 vehicles. For this subsidy to realize the $300/kWh cost goal on this schedule, a learning rate of 33% would be required. The current policy production range is thus not likely to bridge EVs to economic competitiveness.

This finding moves the discussion forward to whether or not the government should adopt a new subsidy plan, estimated here to cost $2-27 billion USD when tapered annually. This is a complex issue that connects to the expected benefit of electric vehicles compared to competing avenues for public spending. This dissertation will only take a narrow view of the issue here, restricting the discussion to a comparison with U.S. federal subsidies for corn ethanol. The electric vehicle and biofuel scenarios are not strictly congruent, however many of the expected social benefits of corn ethanol and EV are similar, such as increased energy independence, jobs, and reduced emissions. The ethanol subsidy provides a sense of historical willingness for the federal government to invest in a transport fuel perceived as socially beneficial.

Corn ethanol has been federally subsidized in the U.S. since the early 1970's. The primary form of subsidy from 1970-2011 was a tax credit ranging from 40-51 cents per gallon. In 2011, the direct subsidy expired, and corn ethanol is now indirectly subsidized through the Renewable Fuels Standard, which mandates a schedule of production targets for ethanol (Environmental Protection Agency 2013). The General Accounting Office estimates the sum of federal subsidies from 1970-2000 totaled $7.7-11.7 billion USD (General Accounting Office 2000). Ethanol production grew rapidly in 2000 onwards, increasing from 1.62 billion gallons in 2000 to 13.9 gallons in 2011 (Energy Information Administration 2013). Subsidy investments increased accordingly, ranging from $1-5 billion USD annually after 2001 (Cox and Hug 2010). This results in a total subsidy cost of around $40 billion USD over the full life of the subsidy program from 1970-2011. Viewed through the narrow lens of the biofuels subsidy policy, even the upper end of the range for EV subsidies – $27 billion USD – is well below what has been historically spent on ethanol. Considering that technological learning suggests that the subsidy holds promise to be a one-time, rather than ongoing, expense, a lithium-ion battery program seems an attractive investment.

In addition to the net sum the federal government is willing to invest in EV subsidies, there is also the critical question regarding tapering schedules. Direct ethanol subsidies continued at similar levels for a period of decades and then were cut to zero in 2011. Mitigating the net cost of the electric vehicle subsidy requires tapering. At the same time, industry requires a certain degree of stability in subsidies to justify long-term investments. Tapering that depends entirely on the shifting political winds in Congress is problematic for industry confidence. While a degree of adaptability is desired, a schedule for tapering based on observed and projected cost reductions, such as an experience curve, is a way forward.

2.3.6 Discussion of Uncertainty

While this study has provided an initial assessment of the range of expected costs for an electric vehicle subsidy program, there are a number of issues not addressed here that should be clarified in future work:

Using the right experience curve – First, decision-makers might consider the resulting range in the net cost of EV subsidy programs cost unacceptably large. Even if the worst-case cost were deemed acceptable, it is possible that learning rates could fall outside of our plausible band of 9.5-22%. Also, it could be that a more complex experience curve relationship is appropriate for lithium batteries. Research to better understand past and potential future cost reductions in lithium-ion battery production could address these uncertainties. This research must be completed for EV policy to succeed. A research investment of hundreds of thousands to a few million dollars could do much to clarify a subsidy program that could run in the billions of dollars.

Beyond battery price – Price is by no means the sole determinant of desirability of a vehicle. The limited range of electric vehicles, for example, is an important performance gap that influences consumer decisions. While plug-in hybrids effectively address this issue, the need for hybrid drivetrain adds to vehicle price. If the subsidy successfully drives adoption of EVs, other benefits may follow, such as increasing familiarity with, and reducing perceived risk of, EVs, and the addition of charging infrastructure, thereby mitigating consumer range anxiety with plug-in vehicle purchases.

Heterogeneous markets for electric vehicles – the constant $300/kWh target assumes a homogeneous market for electric vehicles. Regional differences in gasoline prices and individual differences in driving patterns and vehicle preference presumably result in a heterogeneous market. If consumers in more favorable sub-markets adopt EVs first, public subsidy can be reduced since the willingness to pay of first adopters is higher. Herron and Williams (2013) developed a method to analyze the geographic heterogeneity of markets for residential fuel cells. An extension of this approach to EV markets could clarify how a lower subsidy could succeed in realizing economically competitive EVs.

2.4 Conclusions and Recommendations

Lengthening the subsidy interval increases public investment, more so given lower learning rates and correspondingly high subsidy requirements. These results inform a multi-criteria decision on the appropriate tapering interval. Government budget offices prefer a shorter interval to reduce expenditures, but subsidy program administrators prefer longer intervals and corresponding reduced work to update. Producers prefer a longer interval to justify capital investments. Shorter intervals may actually encourage consumers to purchase due the creation of concrete expiration dates for discounts. The appropriate interval will thus depend on the technology and associated preferences of producers and consumers. Factors other than net investment cost are not analyzed here, but they are noted as important topics for future work.

Subsidy costs are sensitive to learning rate. There is roughly a factor of 10 difference in net public subsidy using the IEA reported learning rate for lithium batteries versus our value obtained from consumer electronics' batteries. This uncertainty is important to manage in the policy process. If a subsidy is implemented based on expectations of rapid learning that are not achieved, political support could wane and the subsidy withdrawn before the technology reaches its potential. One way to mitigate this uncertainty is for governments to invest in estimating learning rates before putting a subsidy program into place. This option is particularly useful in the United States since many lithium-ion batteries used in the US are manufactured there. Spillover effects from international production and consumer electronic battery manufacturing could be accounted for in this scenario as well. Budgeting assuming more pessimistic assumptions for learning rate mitigates the risk of future overspending, but also makes the subsidy less politically palatable. Such tensions are at play in every debate on public investments, our role here is to point out the importance of learning rate in the net investment in the subsidy.

Subject to the uncertainties and model improvements discussed in section 5, results with the current model indicate a subsidy price of 2.1 – 34 billion USD, depending on tapering and learning rate. If reaching the cost target of $300/kWh implies that EVs become attractive to mass consumer markets causing increased adoption and diffusion, this range of program costs is a one time public investment to develop EVs to competitiveness. Whether this sum is an appropriate expenditure of public funds depends on the externality benefits per EV and the degree to which EVs are adopted after becoming competitive to an average consumer (i.e. the market saturation point). The former has been studied by Michalek et al. (2011), though it fair to assert that there is much work to improve the certainty of externality valuation models.

Chapter IV provides a detailed analysis of the potential for subsidies to activate broad technological diffusion and also quantifies the potential environmental benefits of a subsidy program using a case study of plug-in hybrid electric vehicles. The results are similar to those in the current chapter, showing that incorporating technological progress is beneficial to program development. Chapter IV also expands on the assessment of benefits to include the total societal benefits of a subsidy program based on the adoption of plug-in hybrid electric vehicles, even after the subsidy has been removed.

III. Residual Learning Rates in Lead-Acid Batteries: Effects on Emerging Technologies

3.1 Introduction

As the world moves into a data-driven future immersed in digital technology, new constraints are imposed on our infrastructure systems. In the case of electricity, reliability has become a premium service, with governments, hospitals, data centers, corporations, and personal mobile technologies requiring a higher quantity, and a better quality of service than ever before. Many organizations, including electric utilities themselves, are now turning to energy storage systems to provide much needed energy security.

In the world of batteries, the lead-acid chemistry is the most common (Haas and Cairns 1999; Linden 2010). Lead-acid batteries were first developed in 1860 by Gaston Plante and have grown into the most widely used electrical energy storage system due to their high reliability and low cost (Huggins 2010). As shown in Table 4, compared to other energy storage technologies, lead-acid batteries remain one of the cheapest options, giving them a distinct advantage in popular applications.

Energy Storage Technology	**Cost per kWh**
Lead-Acid Batteries	$160
Lithium-Ion Batteries	$600[a]
Sodium-Sulphur Batteries	$450[b]
Flywheels	$600[c]

Table 4. Cost, in $/kWh of various energy storage systems

Data sources: a - (Matteson and Williams 2014; International Energy Agency 2013), b - (Díaz-González et al. 2012), c - (Hadjipaschalis et al. 2009)

The two primary uses for lead-acid batteries are in automobiles and uninterruptible power supplies (UPS) (Haas and Cairns 1999). The size of both the automobile and UPS markets have led to massive deployment of lead-acid batteries, causing further reductions in cost due to technological learning and economies of scale. The main result of this growth has been a strong hold of lead-acid on the battery market for decades. However, due to the recent growth of electric vehicles, which are expected to primarily utilize lithium-ion battery chemistries, and the development of new back-up energy storage technologies, it remains to be seen whether lead-acid batteries can maintain their hold on the electrical energy storage market. Future costs of energy storage technologies are particularly critical given the increasing drive to integrate intermittent renewable energy production into the electrical grid.

The relative cost of lead-acid versus emerging storage technologies is an important factor in determining what storage technology will be successful. It is typically (often implicitly) assumed that learning in lead-acid battery production is finished. The literature analyzing the price-point goal for emerging energy storage technologies refers to a static value of current lead-acid battery prices (Bayunov et al. 2010; Department of Energy 2013; Gyuk et al. 2013; Haas and Cairns 1999; Howell 2012). If, however, lead-acid battery prices can be expected to fall in the future, the competitive price point for emerging technologies is a moving target, as opposed to a stationary one. A moving target could have radical effects on energy storage markets. If a venture firm developing a storage alternative must beat a future reduced cost for lead-acid, this could imply much higher capital and time required to reach cost parity. The firm could face bankruptcy if not prepared for such dynamic market conditions.

Given this context, historical price and production data are analyzed to develop a retrospective forecasting model for future reductions in the cost of lead-acid batteries. The analysis begins by using the standard experience curve that describes total costs decline as a power law function of cumulative production (Neij et al. 2003). As will be seen, the standard experience curve does not reliably reproduce historical costs, leading to the need for an alternative model. A modified experience curve is proposed that separates total cost into material and residual portions, and fits a power law to the residual costs. This model is motivated by the observation that the materials content of lead-acid batteries has been nearly constant for decades and that volatility in materials prices has significantly affected prices of lead-acid batteries. The minimum theoretical cost of the batteries, called the asymptotic cost, is also calculated based on the maximum potential energy density of the primary lead-acid battery chemistry. This value allows for the determination of how far current technology is from its theoretical potential, and also begins a discussion on the practical capabilities of a technology to achieve its maximum potential.

Having constructed a model that reasonably describes historical costs for lead-acid batteries, the results are extrapolated to the future to explore the implications of cost reductions on markets for alternative storage technologies. Drawing on recent work on experience curves for lithium-ion batteries (Matteson and Williams 2014), the effect of future cost reductions in lead-acid batteries on the investment and progress needed for lithium batteries to be price competitive to lead-acid for bulk storage is estimated. The implications of these results are analyzed, specifically regarding policy that aims to develop new technologies in energy storage.

This research provides the following contributions to the literature. By proposing a modified form of the experience curve, the first documented experience curve for lead-acid batteries is defined. This method will find applications for other technologies as well.

Combining the forecast of cost reductions for lead-acid with prior work on lithium batteries provides a concrete example of how learning in an incumbent technology could influence the development of an emerging one. The results have specific implications for energy storage and also illustrate a general phenomenon for technology emergence in energy systems.

To comment on the scope of the analysis, only price (in $/kWh) of a storage technology is considered. While price is a critical indicator of success in the energy storage market, other characteristics of a technology are also important. Performance characteristics such as energy density, power, and cycle life affect what batteries can be used for what application. Also, the environmental impact of energy storage technologies has been an area of concern in recent years as countries attempt to move toward a more sustainable energy system. As a result, some studies have analyzed the environmental impact of various energy storage technologies, such as (McKenna et al. 2013; Notter et al. 2010; Rydh 1999), while others have assessed the impact of environmental policies on energy storage technology development (Ainley 1995; M. C. McManus 2012). While these considerations are important, to reasonably bound the analysis, this chapter focuses only on the price factor.

3.2 Methodology

3.2.1 Residual Experience Curve

This analysis utilizes equation 1 and equation 2 described in chapter 2 to construct the experience curve and learning rate for lead-acid batteries respectively. However, the simple experience curve equation, equation (1), will not robustly reproduce historical battery costs. To address this, lead-acid battery material costs are disaggregated from the experience curve to analyze whether the experience curve fit improves when volatile materials cost data is removed. This method of disaggregation is called forming the residual experience curve. The residual experience curve represents all the technology production costs leftover once materials costs are removed. This also allows us to identify the portions of the technology that are learning. The same methods are used to construct this curve as the previous lithium-ion battery experience curve, with a slightly altered formula, shown in equation 3.

$$C_R\,(P) = C_{R0} * (P/P_0)^{-\alpha} \tag{3}$$

Where

$$C_R\,(P) = \text{Residual Costs} = \text{Total Battery Price} - \text{Materials Costs} \tag{4}$$

and

$$C_{R0} = \text{Initial Residual Cost} = \text{Initial Total Battery Price} - \text{Initial Materials Costs} \tag{5}$$

Once the residual experience curve has been constructed and the residual learning rate is found, equation 6, as recreated from (Herron and Williams 2013), is used to create an improved total battery experience curve that accounts for material costs and residual learning separately.

$$C\,(P) = C_M + (C_0 - C_M)*(P/P_0)^{-\alpha} \tag{6}$$

Where C_M is the materials costs (the non-learning component), α is the residual learning rate (found using equation 3), and all other variables are the same as equation 1. The new experience curves form a better fit with the data and allow us to account for the incompressible materials costs in battery production. The results from equation 6 will be presented later, and are used to project lead-acid battery costs into the future as compared to lithium-ion batteries, as shown in Figure 13.

3.2.2 Learning in an Incumbent Technology

Using lithium-ion batteries as an example, this section will determine how learning in lead-acid batteries, the incumbent technology in the energy storage market, may influence the development of an emerging technology. This is done utilizing a gap-to-parity approach, which is essentially calculating the area between the experience curves for new (lithium-ion) and incumbent (lead-acid) technologies. The larger the area between the curves, the greater investment is needed in the new technology for it to reach parity with the incumbent. Equation 7 shows the formula for the gap-to-parity calculation.

$$Gap\ to\ Parity\ =\ \int_a^b C_{LI}(P) - C_{LA}(P)dP \tag{7}$$

where *a* is the initial level of production, *b* is the level of production where the experience curves intersect, and $C_{LI}(P)$ and $C_{LA}(P)$ are the disaggregated experience curve formulas (from equation 6) for lithium-ion and lead-acid batteries respectively.

3.2.3 Assessing Future Development Potential

Asymptotic cost assessment methods are used to quantify the potential for future cost development in lead-acid batteries. The maximum theoretical energy density for the most common lead-acid battery chemistry is taken as a way to assess the minimum material input requirement for the batteries. The higher the theoretical energy density, in watt-hours per kilogram, the less material inputs required to meet a given energy output. Using current cost trends and the previously mentioned bill of materials, it is possible to calculate the minimum theoretical production cost (materials only) of lead-acid batteries. For example, if the theoretical energy density of the battery chemistry is twice the current energy density, only half the quantity of material inputs will be required to produce the same energy output.

The distance the current technology is away from this result is one way to determine the potential for further technological and cost improvement for lead-acid batteries. However, this does not comment on the practical capabilities of producers to reach the theoretical cost targets. As with many mature technologies, lead-acid batteries have seen little improvement in energy density over the years, consistently remaining around 30-40 Wh/kg (Huggins 2010; Linden 2010). This fact, along with the consideration that improvements may not be cost-effective for producers, mean that lead-acid batteries may have a lower probability of reaching the theoretical maximum energy density.

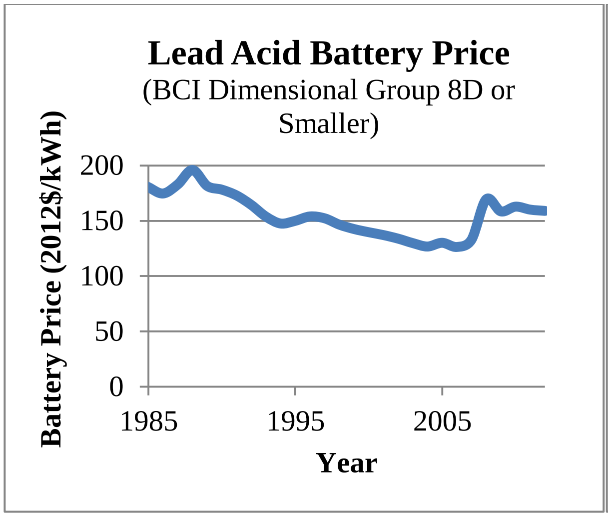
3.2.4 Cost and cumulative production data

The analysis is performed on lead-acid batteries using data for two size separate size groups: 1) small batteries up to the size of an automotive battery – classified as BCI (Battery Council International) dimensional group 8D and smaller – and 2) large batteries, which include heavy-duty batteries, UPS batteries, etc. – classified as batteries larger than BCI dimensional group 8D. These two size groups cover the most popular applications for lead-acid batteries and allow trends in learning for batteries of different sizes to be viewed separately.

In order to produce an experience curve model and determine the learning rate of an energy technology, two types of data are necessary. First, historical data on the cost of the technology must be found for a significant amount of time, usually on the order of decades. Second, data must be collected on the production of the energy technology. Regardless if the production data collected is on a per year or cumulative basis, the data must be converted into cumulative production values in order to be used within the model given by equation 1.

Data from the United States Geological Survey (Wilburn and Buckingham 2006) shows that U.S. production accounts for over 80% of the lead-acid batteries consumed in the U.S. by weight. The geographical bounds of the analysis are set as costs and production in the United States. Price data for the experience curve model was found using historical data from the Producer Price Index (PPI) (Producer Price Index 2013; Producer Price Index 2014), and can be found in Table A1 of Section 6.2 of the Appendix. This data was collected for lead-acid batteries both larger than automotive batteries, and of equal or smaller size than automotive batteries. The PPI data follows cost trends in a technology relative to a base year, in this case 1984. The data initially presents cost in each year as a percentage of the base year cost. For example, the base year PPI cost will always be 100, and should the nominal price of the technology increase, the PPI cost will show a value of over 100 and vice versa.

Once the price data was collected from the PPI, it was transferred from 1984 terms into a real 2012 dollars cost index using year-by-year inflation data (Inflation Calculator 2013). With the $/kWh price in 2012 as the reference year, the real dollar cost in each year is calculated from the literature (Moseley 1998; Schoenung and Hassenzahl 2003). The resulting cost calculations are shown by figures 8a and 8b, for use in equation 1.



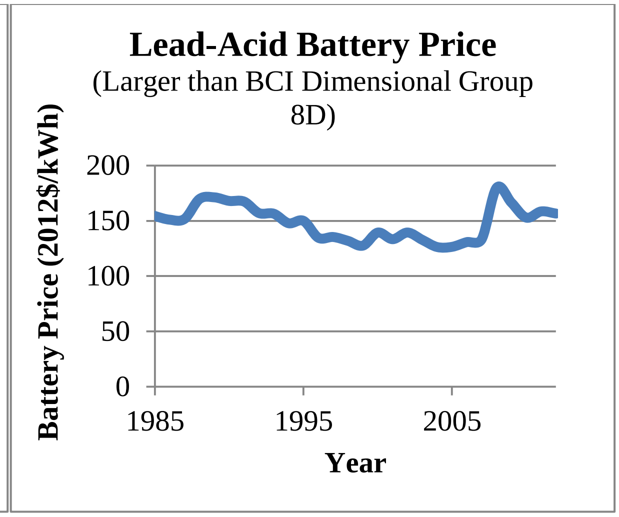


Figure 8a and 8b. Prices of lead-acid batteries in the U.S., 1985-2012 for a) smaller size (e.g. automotive) and b) larger size (e.g. uninterruptible power supply)

Data was taken from references (Wilburn and Buckingham 2006) and (United States Geological Survey 2005) regarding the amount of lead, in kilograms, contained in lead-acid batteries. Linden (2010) calculates that lead makes up about 60% of the battery by weight, allowing us to divide the weight of lead in lead-acid batteries by 0.6 to find the total weight, in kilograms, of lead-acid batteries produced in a given year. This quantity is then multiplied by 0.035 kWh/kg, the average energy density of lead-acid batteries over this period (Linden 2010), to find the total quantity, in kilowatt-hours, of lead-acid batteries produced. Figure 9 shows the results of this calculation over the period from 1975-2012. When these tasks have been completed the price and production data are in the necessary form to make use of equation 1.

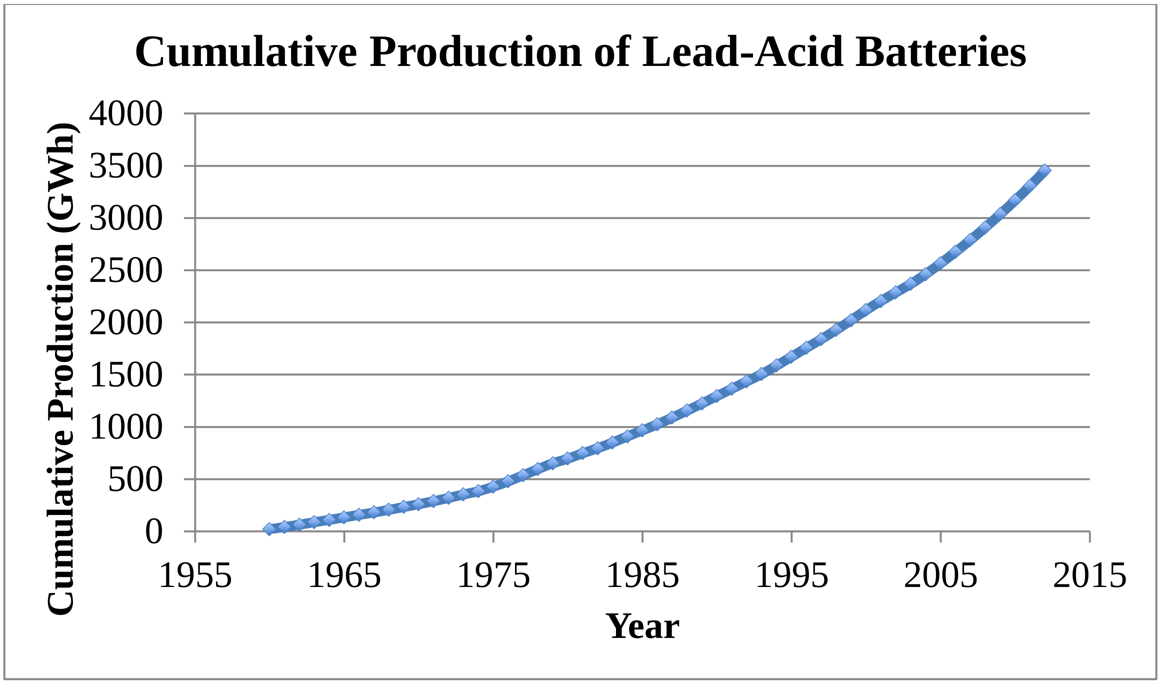


Figure 9. Cumulative production, in Gigawatt-hours, of lead-acid batteries in the United States, from 1975-2012, reconstructed from (EPA 1987; Wilburn and Buckingham 2006; United States Geological Survey 2005)

3.2.5 Materials Cost

The next step in the analysis is to disaggregate the cost data input into the experience curve model so that this section may assess how materials prices may affect overall technological learning. The first step is to identify the materials that form the lead-acid battery. This information was found in reference (Rydh 1999), and shows the list of material inputs for lead-acid battery production. Table 5 shows the material inputs for lead-acid battery production, along with the relative quantities per kilowatt-hour, and the reference used to calculate materials costs. In addition to the inputs shown in Table 5, additional inputs of undisclosed materials, representing 3% of the battery weight per kilowatt-hour were omitted from the analysis due to lack of sufficient data.

Material Input	**Quantity (in kg/kWh)**	**Cost Reference**
Lead	17.5	(“Lead Prices” 2014)
Water	3.8	Assumed to be 0
Sulphuric Acid	2.7	(Sell 2012; Weatherlake 2014)
Polypropylene	2.3	(“Polypropylene” 2014)
Sb, Sn, As	0.6	(“Tin Prices” 2014), (“Pricing” 2013; “Arsenic Prices” 2014)
Polyethylene	0.6	(“Polyethylene” 2014)
Polyester	0.1	(“Polyester” 2014)
Copper	0.1	(“Copper Prices” 2014)
Total	**27.7**	Sum of the Above

Table 5. Material inputs (Rydh 1999), in kilograms, and costs required for each equivalent kilowatt-hour of lead-acid battery

Historical cost trends are found in the literature for each input and used to construct a materials cost trends for lead acid batteries. This trend curve may then be compared to the experience curve as a preliminary assessment of how materials costs may influence technological learning models. Particularly in the material intensive battery industry, materials cost volatility may be expected to influence technology prices, negatively affecting the statistical fit of an experience curve model to the cost curve. This observation may be even more important due to the recent cost volatility in many material inputs for lead-acid battery manufacturing.

3.3 Results

3.3.1 Fitting data to the traditional experience curve

Following the methods described above, this sections tests empirically if the traditional experience model, equation 1, is suitable to describe historical trends. The data and empirical fit for lead-acid batteries is shown as a log-log plot in Figures 10a and 10b below. The resulting curve shows a volatile progression of costs relative to cumulative production. For small lead-acid batteries, the value for the learning coefficient, α, is given by the slope of the trendline, which, is -0.159. Using equation 2, the average learning rate for small lead-acid batteries from 1985-2012 is calculated to be 10%. However, due to the initial volatility of the experience curve, the resulting R-squared value of the trendline is 0.17. This provides very little confidence or certainty in the learning rate calculated through this experience curve.

To show the degree to which the 2007 spike alters the R-squared value of the small battery trendline fit, the experience curve for the years before 2007 has been calculated. When the volatile data from 2007 onward is removed from the model, the R-squared value improves from 0.17 to 0.91. Also, α improves from -0.159 to -0.307, representing a change in learning rate from 10% to 19%, respectively.

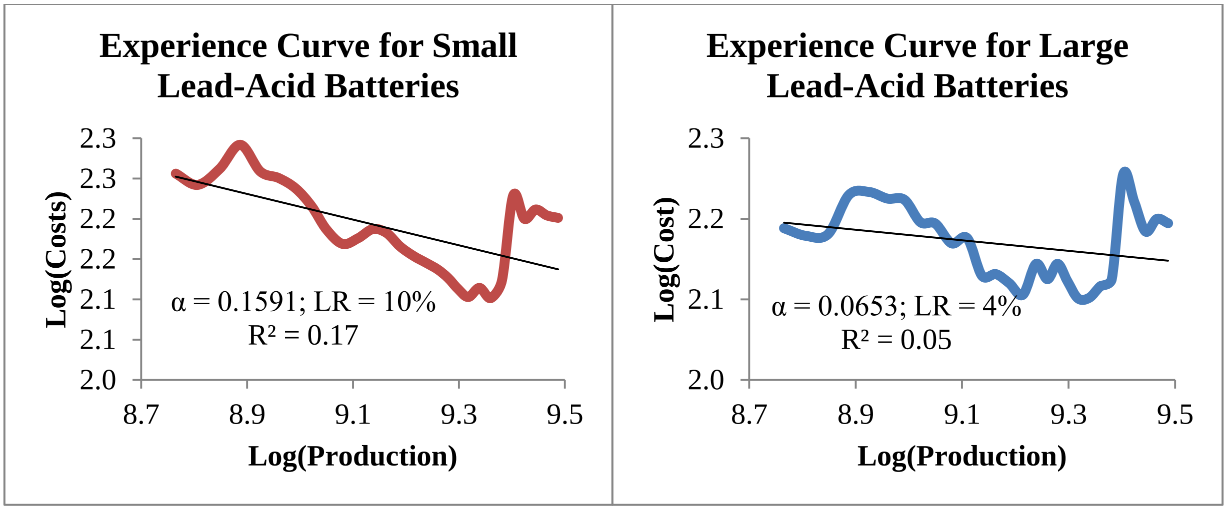


Figure 10a and 10b. Price and cumulative production data fit to traditional experience curve, equation (1), from 1985-2012, for a) smaller size (e.g. automotive) and b) larger size (e.g. uninterruptible power supply)

Next, analyzing larger lead-acid batteries, BCI dimensional group 8D, figure 10b shows the results for fitting the traditional experience curve to historical data. Similar to the results for smaller batteries, significant price oscillations cause a very poor fit to the learning curve model. The value for α in Figure 10b, 0.065, results in an average learning rate of 4%, although this time the R-squared value is calculated to be 0.05, even lower than Figure 10a. However, removing the years after 2007 once again results in a much better fit to the curve, showing more consistent learning from 1985-2006. This new experience curve results in a value of 0.19 for α, representing a learning rate of 13%. The R-squared value has also improved to 0.68 from 0.05 in Figure 10b. Unfortunately, in the case of both small and large lead-acid batteries, when constructing an experience curve, one cannot simply remove segments of data in order to clean up the results. However, this exercise has shown that a majority of the data collected for this study provides clear technological learning in lead-acid batteries. The following sections work to explain the disruption of the learning curve.

3.3.2 Materials Costs

In Figures 10a and 10b the primary culprit responsible for the poor fit is a spike in the cost parameters at the end of the curve, which is visible over the value of 9.4 on the x-axis. When considering this spike in the data, it is noted that it occurs around 2007, and prices still have not recovered to the original levels shown on the curve. One explanation for the volatility in the experience curve is fluctuations in materials price that cause unpredicted increases in production cost. In order to address this issue and improve the fit of the experience curve to the data the effects of material costs will now be analyzed by calculating material cost trends for all of the primary material components of lead-acid batteries, as described in Table 5. If this hypothesis is successful, the effect should be a large spike in materials costs around 2007. This spike would cause volatility in the experience curve, and the poor fit to our model shown above.

Using a variety of data sources, shown in Table 5, cost trends for the material components of lead-acid batteries are quantified. By identifying key inflection points, this information will lend insight to the drivers of the battery cost curve, and potentially help us solve the issue of volatility in the experience curve. Due to data constraints, only materials costs back to 1989 were considered. Figure 11 shows the trends in materials costs for lead-acid batteries, separated into Lead Cost, and Other Materials Costs.

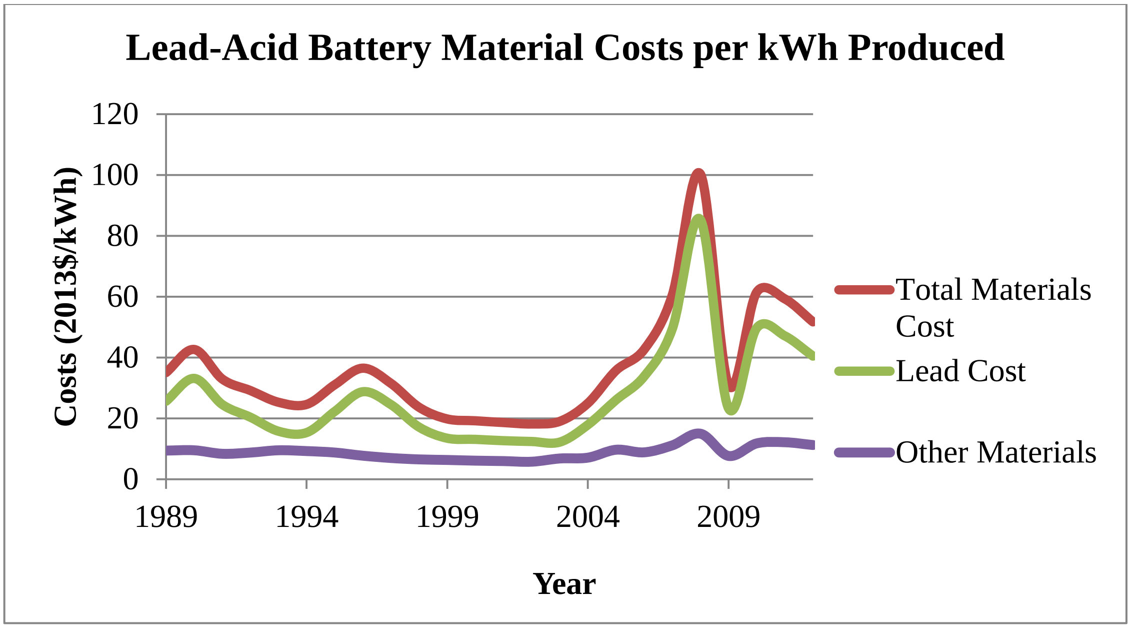


Figure 11. Materials Costs per kWh of lead-acid batteries, 1989-2012, separated into Lead cost, all other materials, and total materials costs.

There are two primary conclusions to be drawn from Figure 11. First, the chart shows relatively consistent decreases in non-lead materials costs up until the beginning of the cost spike in 2004. This observation is consistent with the previously determined experience curve. The second, and more obvious conclusion is that there were drastic increases in materials cost, potentially solving the issue of volatility in the experience curve. However, there is uncertainty as to what degree material costs influenced technological progress unless the material costs are incorporated into the learning model itself. As previously mentioned, this analysis seeks to do this by subtracting materials costs (Figure 11) from overall battery costs (Figures 8a and 8b) and fit this residual cost to the learning curve model (equation 1).

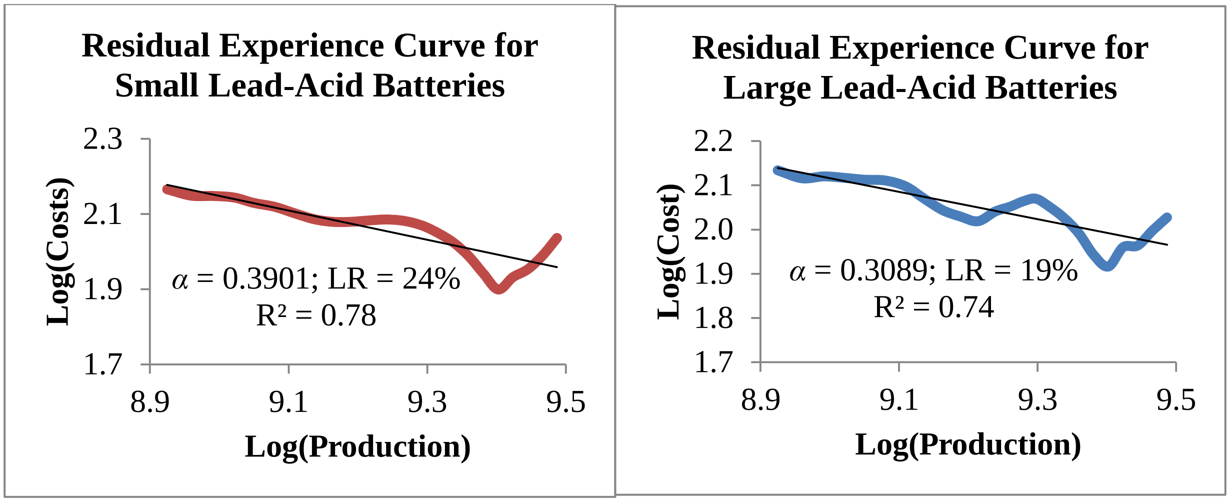
3.3.3 Residual Experience Curve

In addition to pulling out residual from material costs, this assessment considers various moving time-averages of annual data. In these cases a grouping of 2 or 4 surrounding years were averaged together to determine each individual year's value. Figures 12a and 12b show the results of constructing the residual experience curve, equation (3), for small lead-acid batteries from 1989-2012.

The primary concern is with how Figures 12a and 12b (residual experience curves) behave as compared to Figures 10a and 10b (original experience curves) respectively. The residual experience curve shows a better fit to the trendline, with an R-squared value of 0.779 in figure 12a compared to a value of 0.17 in Figure 10a. Also, removing the volatile material costs improves the learning rate observed in the residual curve as compared to the total-battery learning rate shown in Figure 10a. The value for α in Figure 12a, 0.3901, results in a learning rate of around 24% for the residual costs in lead-acid battery production.

The remaining volatility in the residual learning curve can be explained by material price shock. From 2004 to 2007, lead-acid battery materials costs increased by 400%. The effects on total battery costs were subdued to an increase of only 20%, due to the reactive 30% decrease in residual costs (the downward spike above 9.4 in Figures 12a and 12b). Essentially, residual prices were forcibly held down in order to keep lead-acid battery costs to a minimum during the material price shocks. Since that point, Figures 12a and 12b show some continued oscillation around the experience curve as material costs (from Figure 11), and thus the residual costs, begin to retract to pre-2007 values.

Figure 12b shows the residual experience curve for large lead-acid batteries, from 1989 to 2007. In comparison to Figure 10b, this curve shows both a better fit to the data as well as a larger learning rate. The R-squared value improves from 0.05 in Figure 10b, to 0.736 in Figure 12b, an even larger improvement than was shown in the case of small lead-acid batteries. Also, the new learning rate is calculated to be 19%, up from 4% previously.



Figures 12a and 12b. The residual experience curve (experience in total costs – material costs) for small and large lead-acid batteries, for 1989-2012, with a 4-year time averaging.

Removing material costs from the experience curve has a significant effect on the observed learning trends in large lead-acid batteries. These results show that removing volatile material costs from the lead-acid battery experience curve improves the model's fit to the available cost and production data. While overall volatility in the experience curve is less than ideal, an improved fit may offer more opportunities for future analysis.

3.3.4 Comparing traditional and residual cost experience curve models

Table 6 compares the results of traditional and residual cost learning for small and large lead-acid batteries. To keep all the results on an even field, each scenario is analyzed over the same time period, which, due to material cost data availability, has been chosen to be 1989-2012. Included in the table are the aggregation level of the battery that is analyzed (i.e. total battery or residual), time step used when constructing the experience curve, R-squared value of the model fit, improvement of the model fit when using the residual experience curve, and the resulting learning rates. The time step tells the number of years used in each case to form the moving average curve of the cost data. For instance, a time step of two means the results being presented are for a two-year moving average assessment of the given technology. The moving average presentation is another way to mitigate variability in the year-to-year data set.

Battery Size	Time Step (Years)	Aggregation level	R^2	Learning Rate
Small	1	Total Battery	0.17	7.6%
		Residual	0.51	22%
	2	Total Battery	0.26	9.5%
		Residual	0.63	23%
	4	Total Battery	0.44	12%
		Residual	0.78	24%
Large	1	Total Battery	0.05	4.2%
		Residual	0.41	18%
	2	Total Battery	0.09	5.5%
		Residual	0.57	19%
	4	Total Battery	0.18	6.9%
		Residual	0.74	19%

Table 6. Complete results of the learning assessment for all lead-acid batteries including residual cost learning. All results are for the time period 1989-2012.

In each instance, using moving averages to reduce year-to-year data variability increased both the R-squared value and the learning rate. In both small and large lead-acid batteries, the learning rates experienced in residual costs far exceed those found at the battery level. For small lead-acid batteries, residual learning occurs about twice as fast as total battery learning, while for large lead-acid batteries, residual learning occurs around four times faster than total battery learning.

On the whole, small lead-acid batteries seem to have experienced learning at a higher rate than large batteries from 1989-2012. Learning rates in large batteries are less than half of their small battery counterparts, though when calculating residual learning effects, this gap closes significantly, resulting in residual learning rates within 20% of those calculated for small batteries. Overall, learning rates for the entire lead-acid battery market should lie somewhere between these two cases, since the market is made up of some combination (e.g. 50-50 or 60-40) of small and large lead-acid batteries.

3.3.5 Asymptotic Cost Assessment

The maximum theoretical energy density of a typical lead-acid battery is 175 Wh/kg (Huggins 2010). This value is five times the current energy density, meaning that if lead-acid batteries were to reach this potential, battery production would require 80% less material inputs than are used in current battery production. Using current materials cost data from Table 5, the minimum potential cost, called the asymptotic cost, of lead-acid battery production is calculated.

At current price points, the asymptotic cost of a lead-acid battery is found to be \$11/kWh. The current materials cost, as shown in Figure 11, is around \$53/kWh. This means that, learning effects aside, energy density improvements have the ability to reduce materials costs by around 79%. This seems an encouraging result, although since lead-acid battery energy density has long been stagnant, the practical potential for improvement may be significantly less than is shown by the asymptotic cost assessment.

3.4 Discussion

3.4.1 Lead-Acid Battery Learning Compared to Other Energy Technologies

In this section, the results are applied to a broader assessment of the energy storage market, including a comparison with lithium-ion batteries. This allows us to better grasp the market implications of our new information, and how emerging technologies may be affected. The results outline our calculations for how lead-acid batteries have experienced technological learning over the past few decades. While this may be the first experience curve assessment completed for lead-acid batteries, many other studies have been conducted on other energy technologies. In order to place lead-acid battery learning in perspective, Table 7 has been constructed to show how learning rates in lead-acid batteries compare to other energy technologies.

Energy Technology	Learning Rate
Lead-Acid Batteries, Small (Residual)	23%
Lead-Acid Batteries, Large (Residual)	19%
Lithium-Ion Batteries	22%[a]
Natural Gas	12%[b]
Nuclear	9.0%[b]
Photovoltaics	22%[b]
Wind	12%[b]

Table 7. Learning rates of various energy technologies; a - (Matteson and Williams 2014) b - (Weiss et al. 2010)

The learning rates for lead-acid batteries are comparable to learning rates in other energy technologies. When volatile material costs are removed, the residual learning rate calculated for lead-acid batteries resembles those for other fast-learning technologies like lithium-ion batteries and photovoltaics. However, when material costs and learning are considered as a whole, lead-acid batteries rank near the bottom in terms of learning rates.

As other energy storage technologies are developed, lead-acid batteries will have a growing number of competitors in the marketplace. Learning studies such as this one will be important to inform policy and forecast potential winners and losers in the competition for economically viable energy storage technologies. If material cost volatility continues to hinder lead-acid batteries and other technologies, such as lithium-ion batteries, continue to progress down their learning curves, lead-acid batteries' hold on the market may begin to diminish. However, if materials costs stabilize and residual learning continues, lead-acid batteries will continue to dominate the energy storage market for years to come.

3.4.2 Materials Costs in Lead-Acid Batteries

Recently, lead-acid battery material costs have spiked and as a result have become the primary determinant of battery costs. The price shocks of 2007 have also impacted technological learning, creating additional difficulties in assessing the learning potential of lead-acid batteries. Within the scope of this chapter three potential reasons have been identified for why materials costs may have such an impact on learning results.

First, future assessment may need to find a way to expand the learning assessment of lead-acid batteries to include more potential cost influences by utilizing one of the many multi-factor experience curve models. Adding additional factors may help identify and incorporate material price volatility into the model to give a learning curve that stays more true to actual events.

The second possibility is that the price volatility was so significant that it has caused changes in production costs and methods, thereby affecting the modeled learning rate in lead-acid batteries. This is a likely result, since materials prices increased 400% from 2004 to 2007. It should be noted that there are many potential explanations for the spike, such as rising costs in other related industries or the overall economic downturn. It is also possible that other products, such as lithium-ion batteries could experience similar spikes, due to materials scarcity and other economic factors. In this case, procedures such as ours, which attempt to mute material cost affects by constructing a residual experience curve, are one option for completing a technological learning assessment.

The final potential explanation is that learning in lead-acid batteries is over, and from this point on any technological learning is a figment of variations in material costs. If this explanation were true, the inflection point in 2007 would signify the "end" of lead-acid battery learning. With no more learning effects a close correlation would exist between material costs and total costs of lead-acid batteries, with each staying stable or increasing at close to inflation rates. It is not possible to tell currently whether this explanation is true, as much more data, including future cost data, would be required to determine whether there are any additional learning effects influencing lead-acid battery costs.

The future outlook of the lead-acid battery market remains dependent on material costs and future developments in other energy storage technologies. One other factor that may have a significant impact in this area is the introduction of new materials or processes for lead-acid battery production. The maturity of the market and the relatively low price point of lead-acid batteries could mean great success for chemistries with similar production requirements and higher energy densities. Moving forward, new lead-acid battery chemistries may be the key to the market's future success against newer battery technologies. Organizations such as the

Advanced Lead-Acid Battery Consortium are already moving in this direction in the hopes of extending the potential for lead-acid batteries in the energy storage market.

3.4.3 The Potential for Future Developments

Section 3.3.5 used an asymptotic cost assessment to show the potential for an 80% improvement in energy density and materials costs. However, due to the long history of lead-acid battery production, use, and development, and the comparatively low current energy density, much of the growth potential may never be reached. Even if lead-acid batteries close in on the maximum theoretical energy density, uncertainties in learning and material costs may still hinder lead-acid batteries in the marketplace. For example, lithium-ion batteries have experienced rapid technological growth and cost reductions in recent years. If these trends continue, and lithium-ion batteries also approach their maximum theoretical energy density of 456 Wh/kg (Haas and Cairns 1999) (for lithium-manganite spinel), lead-acid battery technology may lose control of the energy storage market, both in automotive batteries and UPS batteries.

Figure 13 illustrates the comparison between the learning potential of lead-acid batteries and lithium-ion batteries. Prices for lithium-ion batteries are currently around $600/kWh (International Energy Agency 2013; Matteson and Williams 2014), compared to around $150-200/kWh for lead-acid batteries. However, high materials prices in lead-acid batteries put a cap on the potential for future improvement. As a result, lithium-ion batteries have the ability to catch lead-acid batteries in price, as long as production and technological learning continue at historical rates, and lithium-ion batteries avoid material price spikes similar to those in lead-acid batteries. To predict when this crossover point may occur, the analysis proceeds by bounding lithium-ion and lead-acid battery learning.

The experience curves for lithium-ion batteries were constructed based on data from (Matteson and Williams 2014), using \$600/kWh as the current price, 15% and 22% learning rates, and $7.8x10^7$ kWh of cumulative production. The lead-acid battery experience curves utilized the PPI price data, as well as the production data from figure 6, in the experience curve model shown by equation 6 with residual learning rates of 18% in the low scenario and 24% in the high. Each has a current asymptotic cost of \$50/kWh representing the materials costs shown in Figure 11. Due to their higher energy density, lithium-ion batteries have a much lower current asymptotic cost, which is around \$11/kWh in 2013 USD (Matteson and Williams 2014). Using the model given by equation 6, equations 8–11 show the experience curves illustrated in Figure 13 for lithium-ion, large lead-acid, and small lead-acid batteries respectively.

Lithium-ion High Learning: $$C_{HLI} = \$11 + (\$600 - \$11) \times \left(\frac{P_{Li-Ion}}{7.8x10^7}\right)^{-0.3536} \quad (8)$$

Lithium-ion Low Learning: $$C_{LLI} = \$11 + (\$600 - \$11) \times \left(\frac{P_{Li-Ion}}{7.8x10^7}\right)^{-0.2345} \quad (9)$$

Lead-Acid High Learning: $$C_{HLA} = \$50 + (\$155 - \$50) \times \left(\frac{P_{LLA}}{3.5\,x10^9}\right)^{-0.3960} \quad (10)$$

Lead-Acid Low Learning: $$C_{LLA} = \$50 + (\$155 - \$50) \times \left(\frac{P_{SLA}}{3.5\,x10^9}\right)^{-0.2863} \quad (11)$$

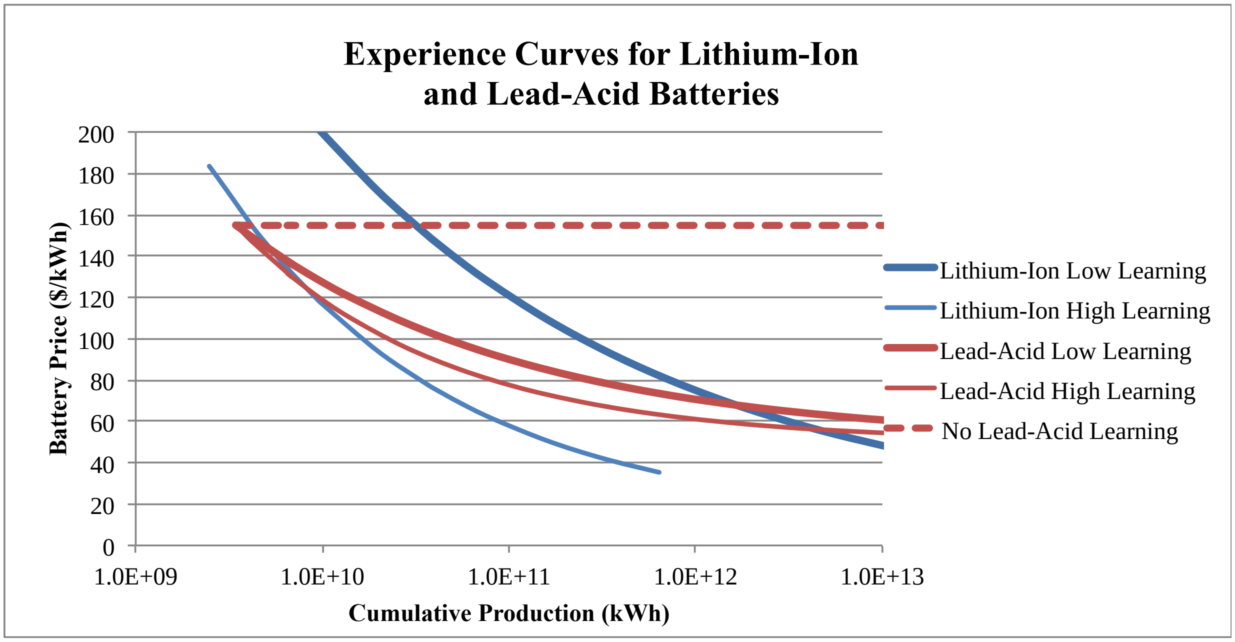


Figure 13. Projected experience curves for Lithium-Ion and Lead-Acid Batteries

3.4.4 Gap-to-Parity Analysis

The developments illustrated in Figure 13 are important not only to lead-acid battery producers, but also to the producers of other energy storage technologies and the government as well. Costs and learning in these important energy technologies must be monitored in order to develop new applications for these technologies, and also to inform future policy on the usage and incentivizing of energy storage technologies. The goal of achieving "price parity" with an entrenched technology is embedded in the discourse on R&D and subsidy policy for new energy technologies. Focusing on batteries, lead-acid has been the cheap and reliable standard, thus establishing itself as the entrenched technology for emerging ones to beat. Future cost reductions in lead-acid batteries, even only in residual components and processes, implies advanced energy storage technologies must meet a lower price parity.

Considering lithium-ion batteries as an example, if the trends in technological learning continue and lead-acid prices stagnate, lithium-ion batteries will catch up with current lead-acid battery prices at \$150/kWh after 4.1×10^9 kWh of cumulative production. At current growth rates in cumulative lithium-ion battery production, around 25% annually, and lead-acid production, around 5% annually, lithium-ion batteries could surpass this value in 17 years. This would be distressing for lead-acid battery producers and a huge success for proponents of lithium-ion batteries, since this represents a time where lithium-ion batteries would be viable to supplant lead-acid batteries in all applications. However, this study has shown that there is potential for additional learning in the residual components and processes in lead-acid battery production.

Figure 13 shows battery progress accounting for residual learning rates using equation 6. Table 8 details the specific findings of the gap to parity analysis for lithium-ion batteries. The results show that if lithium-ion batteries experience learning rates below the 15% used in the low learning scenario and lead-acid batteries experience any more progress, lithium-ion batteries may never reach parity, simply due to the financial investment required to bridge the gap. Additionally, if improvements are made in lead-acid battery energy density or materials costs, or if lithium-ion batteries fail to perform as expected, the cost parity point may be pushed off further even in the high learning scenario for lithium-ion batteries.

		Crossover Point (Total kWhs)	**Production Gap (kWhs)**	**Gap to Parity**	**Years to Parity**
High LI Learning	No LA Learning	4.1E+09	-	-	17
	Low LA Learning	6.2E+09	2.10E+09	$7 Billion	19
	High LA Learning	1.0E+10	6.80E+09	$18 Billion	21
Low LI Learning	No LA Learning	3.1E+10	-	-	27
	Low LA Learning	1.4E+12	1.4E+12	$1.1 Trillion	42
	High LA Learning	4.0E+12	3.9E+12	$2.5 Trillion	48

Table 8. Gap to parity analysis for lithium-ion batteries using lead-acid batteries as the incumbent technology and various combinations of learning rates for each technology

This new information suggests that lead-acid batteries are likely to maintain a cost advantage over lithium-ion batteries for up to an additional two decades compared to the constant lead-acid battery price scenario. Using equation 7, it is found that this increase in production required to reach parity could result in an additional \$7 – \$18 billion of investment, in the form of battery purchases, needed for lithium-ion batteries to become competitive with lead-acid batteries in the high learning rate scenario. The results from Figure 13 indicate that in competitive markets, lithium-ion batteries must depend on high learning rates, or very low learning rates in lead-acid batteries, to reach parity within three decades and less than \$100 billion in total additional investment. Otherwise, investment in the development of lithium-ion batteries to displace lead-acid would not be recommended.

These results may seem like an ultimatum on lithium-ion battery development, however the primary use and growth in lithium-ion batteries has been primarily in the small mobile battery and plug-in vehicle battery markets. Due to operational constraints, lead-acid batteries do not compete with lithium-ion in these markets, and those batteries that do compete with lithium-ion are more expensive than lead-acid batteries. This relaxes the constraints for lithium-ion batteries in terms of target cost, improving the outlook in the primary sectors. However, should lithium-ion battery manufacturers look to expand their markets to internal combustion vehicles or backup energy storage for UPS systems, they will face difficult competition as outlined in Figure 13 and Table 8. This analysis serves as an example of the consequences of technological progress, residual or otherwise, within incumbent technologies.

3.5 Conclusions and Recommendations

This information is critical to policymakers, investors, and producers concerned with energy storage technologies. For policymakers, successful use of incentives for emerging energy technologies hinges on accurate price tracking and forecasting. Unexpected changes in the distance to parity could result in a failed subsidy program, or require additional funds before institutional goals are met. Investors choose to support growing technologies in the hope of widespread adoption and accompanying profits. Extended timelines to reach parity could result in investors discontinuing support of a technology. Producers rely on technological learning advancements to close the gap between emerging and incumbent technologies. If this gap widens, or closes slower than expected, price parity and widespread adoption of a technology may be pushed into the future, costing additional large sum investments and threatening the viability of crucial future energy technologies.

The idea that cost reductions in an incumbent technology affect the market feasibility of an emerging one is important well beyond the energy storage domain. For example, goal setting for alternatives to the internal combustion engine are typically framed as if no further progress will occur (Plotkin and Singh 2009; van Vliet et al. 2010). There are no doubt cases where assuming a constant incumbent is safe, but our analysis indicates the importance of checking this assumption with quantitative analysis. This chapter argues that analyses such as the one completed here are needed to mitigate risk for research and development and subsidy policies for energy technologies.

IV. Cascading Diffusion and Energy Technology Subsidies: The Case of Plug-in Hybrid Electric Vehicles

4.1 Introduction

Every year, governments around the world spend billions of dollars on subsidies for energy technologies, with the hope of increasing cost-competitiveness in emerging technologies. Through a variety of policy initiatives, the United States spent over $100 billion between 2006 and 2012 to support energy technologies (Dinan and Webre 2012). The magnitude of this public investment proves the importance of evaluating the policies to ensure the funds are not being wasted. However, when these policies are evaluated, a cost-benefit analysis of the items directly subsidized will generally neglect technological progress. Previous assessments of energy technology subsidies, such as Michalek et al. (2011) and Gecan (2012), do not consider technological progress in their evaluations, leading to an underestimation of total social benefits of the policy in question. Other studies consider progress when quantifying costs and benefits, but only over the life of the policy in question (del Rio 2012; Klein et al. 2010; Wand and Leuthold 2011; Ragwitz and Huber 2005), still neglecting to account for one of the primary motivations behind subsidy policy: subsidies are intended to drive consumer adoption, which increases production levels, stimulating technological progress and reducing costs. As the costs continue to drop, subsidies may be adjusted accordingly until market activation occurs and economic incentives are no longer necessary. Once the market for the emerging technology has been activated, diffusion continues until the market reaches saturation. This free, post-subsidy diffusion should be quantified and credited to the subsidy program's economic benefits. Accounting for post-activation diffusion, as well as incorporating technological learning into subsidy formation, can significantly reduce the perceived subsidy cost per unit, as is shown in the proceeding analysis.

This phenomenon is illustrated clearly in the evaluation of the Plug-in Hybrid Electric Vehicles (PHEV) tax credit. Based on the current costs and environmental benefits of the tax credit, Michalek et al. (2011) conclude that the $7,500 per vehicle credit is more than ten times the current net benefits of PHEVs and should therefore be redirected elsewhere. However, this assessment does not consider the environmental benefits of the policy after the tax credit has been removed. Accounting for technological learning and heterogeneous markets for PHEVs allows benefits extending beyond the life of the policy to be quantified through a cascading diffusion assessment.

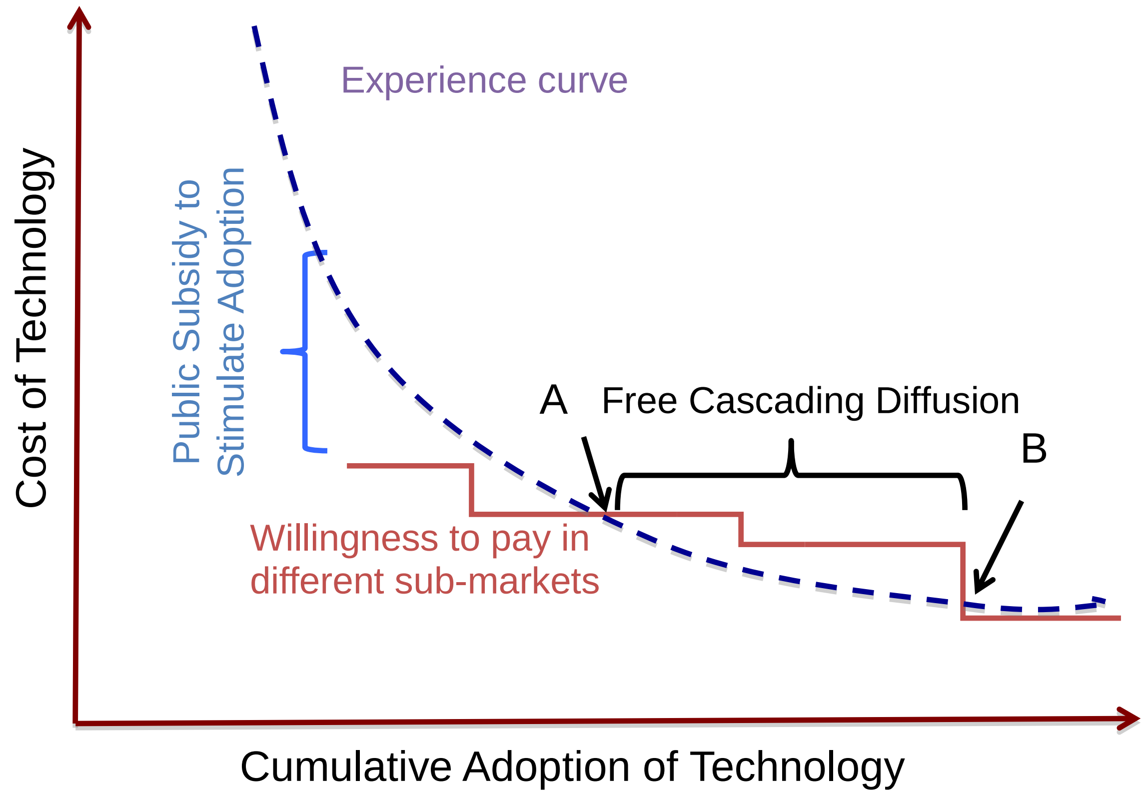


Figure 14. Combining experience curves and market curves for subsidy policy analysis. The area between the experience curve (purple) and the market curve (red) up to point A represents the cost of the subsidy. After market activation at point A, there is "free" cascading diffusion until market saturation at point B.

The literature surrounding PHEVs is primarily split into three categories: studies of PHEV environmental impacts, markets, and subsidies. Studies assessing and predicting the environmental impact of PHEVs include (Bradley and Frank 2009; Mui 2007; Musti and Kockelman 2011; Notter et al. 2010; Samaras and Meisterling 2008; Sioshansi and Denholm 2009; Stephan and Sullivan 2008), while (Michalek et al. 2011; Shiau et al. 2009; Shinoda et al. 2008) analyze the environmental benefits associated with PHEV adoption. The environmental studies assessing the impacts and benefits of PHEVs have shown the potential for vehicle electrification to save on overall fleet emissions. The characterization of this social benefit is a primary consideration in identifying technologies to subsidize. Without the discovery of positive environmental benefits, the technology would rely on other factors to influence the argument for financial incentives, such as reduced oil dependence and the accompanying military and energy security savings, and improved energy efficiency (Waller et al. 2014), which may be a key determinant in economic growth potential (Laitner et al. 2012).

The next category includes articles on consumer purchasing decisions and responses to market growth (Graham-Rowe et al. 2012; Hidrue et al. 2011; Lin and Greene 2011; W. McManus and Senter, Jr. 2009; Ozaki and Sevastyanova 2011; Pellon et al. 2010), and studies assessing the future outlook of the PHEV market (AEA: The Committee on Climate Change 2009; Al-Alawi and Bradley 2013; Cleary 2010; Sovacool and Hirsh 2009; Tal and Nicholas 2013). These studies are important to grasp the potential effects of incentives, and to identify possible barriers to adoption. Outlining the growth trends can also help assess the technology's ability to diffuse through the population of consumers under different conditions. For example, the environmental benefits of PHEV adoption could increase with higher penetration levels of renewable energy in the electricity grid, leading to increased adoption levels in later time periods. Including technological progress and energy forecasting into growth models can improve the accuracy of market projections.

Finally, studies that analyze the formation and effect of incentives for PHEVs include (Crist 2012; Diamond 2009; Kihm et al. 2010; Skerlos and Winebrake 2010). Similar to the second category of sources, these references include discussions of the market for PHEVs, albeit through the lens of policy development and the impact of incentives on PHEV market.

While utilizing information from the first two categories, these sources stand as the current reference for policymakers. However, all of these sources fail to account for technological learning and the influence on subsidy levels. This chapter addresses this issue while incorporating high-resolution data on PHEV submarkets to provide clear recommendations to policymakers regarding subsidy development for PHEVs and other emerging technologies.

Tsuchiya (1989) combines market and experience curves for photovoltaics in order to calculate the subsidy required to bring the technology to price parity. However, this analysis does not construct empirical heterogeneous market curves and only quantifies program costs and benefits up to the conclusion of the policy. Similarly, Duke and Kammen (1999) utilize experience curves to complete a cost benefit analysis of three separate policy programs, based on the difference between the forecasted experience curve value and the environmental benefit of a given technology. This study also neglects program benefits after the subsidy is removed and does not deal in heterogeneous markets. Considering the heterogeneity of markets by analyzing distinct submarkets unmasks trends that would otherwise be hidden by market aggregation.

4.2 Methodology

4.2.1 The Concept of a Subsidy

For a consumer to decide to purchase a new technology requires that the purchase be economically viable and that any non-economic market barriers can be overcome. Economic viability is taken to mean that the purchase is financially beneficial compared to a benchmark product of similar utility (e.g., using Net Present Value to compare a PHEV and a conventional gasoline car). New technologies often face market barriers such as limited product selection, consumer ignorance, or concerns about reliability (Zhai and Williams 2012). Government interventions to promote a socially desirable technology might aim to address economic feasibility, market barriers or both. One approach to overcoming market barriers is to increase a subsidy beyond economic viability to provide an incentive, but there are other possibilities. For example, the special credits given to alternative fuel vehicles in U.S. CAFE Standards act to overcome market barriers by encouraging auto manufacturers to broaden the selection of electric vehicles (NHTSA 2014). The variability and inconsistency of noneconomic market barriers make designing a government subsidy program infeasible, and a government program should therefore focus on empirical economic information to minimize wastefulness in a subsidy.

4.2.2 The PHEV Experience Curve

Treating the cost of PHEV as the gap to parity, technological progress of different components of PHEVs is factored in to the analysis, resulting in equation 12 for the PHEV experience curve. A report from Argonne National Laboratory (Plotkin and Singh 2009) shows that PHEVs experience an \$11,000 total price difference as compared to ICVs, and non-battery, electric drive-specific components make up approximately 14% of the PHEV cost. Within this \$11,000 difference, there is a \$4,000 incompressible, non-learning, cost in the difference between ICVs and PHEVs, comprised of additional machinery required for the hybrid drive, as well as electric-drive components that are presumed to have reached the conclusion of their learning potential. More specifically, this \$4,000 is composed of increases to glider (49%) and transmission cost (8%) for utilization in a hybrid drivetrain, and the addition of electric motor (25%) and controller costs (18%). The remaining \$7,000 of the \$11,000 total price difference is attributed to the battery system and represents the primary learning capacity in PHEVs.

Segmenting the experience curve formula to account for this information results in the asymptotic experience curve in equation 12.

$$C(P) = \$4000 - \$7000\left(\frac{P}{71174}\right)^{\alpha} \tag{12}$$

Without the benefit of extensive historical data on learning rates for PHEVs a bounding approach for potential learning rates is utilized. For the upper bound or optimistic case, a rate of 22% is used, corresponding to a value for α of 0.3536. This value was taken from (Matteson and Williams 2014) and is calculated as the historical learning rate for lithium-ion batteries, the most common form of battery in PHEVs. The pessimistic case used a learning rate of 9.5%, and a value for α of 0.1440. A review of the literature found that this rate from the International Energy Agency (2013) is a conservative estimate and is therefore used as a lower bound.

The value for initial production also comes from the analysis within (International Energy Agency 2013) and represents the cumulative international adoption of plug-in vehicles to 2012. International data is used to account for the expected spillover effects across the international vehicle manufacturing industry. This signifies that our model treats technological progress in PHEVs as an international phenomenon, while applying the model to the situation within the United States. Additional learning factors, such as the effect of mobile and storage battery production on vehicle battery development, have not been included in this analysis.

4.2.3 Incompressible Cost

As stated above, and shown by equation 12, the current manufacture of PHEVs results in an incompressible cost of $4,000 above the cost of manufacturing an ICV. This phenomenon plays an important role in determining the viability of a PHEV subsidy program in different submarkets. This additional cost means that a consumer's willingness to pay for a PHEV must be at least $4,000 for the decision to make sense economically (i.e. for net present value to be greater than zero).

This incompressible cost is also not affected by the learning rate. Changes in the learning rate will only affect how quickly, measured in number of vehicles adopted, the experience curve nears the incompressible cost asymptote. For a willingness to pay above $4,000, the learning rate is essential to determining whether or not the decision will be economical for most submarkets.

4.2.4 PHEV Market Curves

Calculating the subsidy gap then requires determination of the price parity target: the cost that represents economic competitiveness with incumbent technologies. In some cases, the price parity target is homogeneous throughout the population of potential consumers, although the target has the potential to fluctuate significantly based on variability in the economic situation of consumers in different geographic locations. In an effort to mitigate this variability, the price parity target is treated as a heterogeneous value based on the economic willingness to pay of individual consumers. Economic willingness to pay refers to the potential improvement in the economic standing of an individual given the choice to adopt a new technology as opposed to an incumbent. This is calculated by determining the difference in lifetime cost of an emerging technology relative to the cost of the incumbent. If adopting the emerging technology results in a lower lifetime cost, the consumer is said to have a positive willingness to pay equal to the magnitude of the cost savings. Taking it one step farther, combining the willingness to pay of multiple consumers creates a market curve for the emerging technology.

A consumer's willingness to pay for a PHEV is taken to be the total lifetime cost savings as compared to equivalent ICVs. Several different factors determine cost savings for

PHEVs, including annual vehicle miles traveled, gas prices, electricity prices, and the fuel efficiency of the incumbent. Over a ten-year lifetime, and assuming a 10% discount rate, the lifetime savings is quantified as the net present value of the total cost savings, given by the difference between driving an ICV versus driving a PHEV. The ICV is assumed to have an EPA combined fuel efficiency of 30 miles per gallon, which is the average for the top 20 selling cars in the US (Department of Energy 2014), and is significantly above the average fuel efficiency of the current vehicle fleet in the US, nearing the CAFE standards for new vehicles. The PHEV is assumed to have a fuel efficiency of 40 miles per gallon of gasoline and a conservative estimate of 3 miles per kWh of electricity, which is lower than the average performance even during cold winter months when PHEVs are least efficient (Patten et al. 2011). These assumptions correspond to a conservative estimate of consumer willingness to pay for PHEVs in the US.

Proceeding with the analysis, three variations of the PHEV market curves are formulated. First, market curves are developed using data corresponding to nation-level averages of vehicle miles traveled, electricity price, and gasoline price (Energy Information Administration 2014a; Energy Information Administration 2014b; Department of Transportation 2012). Based on the above data, the national average consumer has a willingness to pay of $3,844, which is less than the incompressible cost. Unless a new technology or production method is introduced to change this cost, and create a new experience curve with a lower asymptote, the national average, as well as a significant portion of states (Figure 15) and individual consumers (Figure 16) will never find PHEVs attractive economically.

The second method is augmented to include state-specific average vehicle miles traveled, electricity price, and gas price (Energy Information Administration 2014a; Energy Information Administration 2014b; Baxandall 2013). This approach produces the state-level average consumer willingness to pay, which may be organized in decreasing order to be utilized in the subsidy analysis. The second set of market curves also divulge the ranking of States that find PHEVs most economically attractive, information that is useful when determining optimal diffusion paths for technology adoption.

Finally, the resolution is increased further to take into account the travel characteristics of individual consumers. This third variation of the PHEV market curves utilizes data from the most recent National Household Transportation Survey (NHTS) (Department of Transportation 2011), in which over 300,000 respondents were surveyed regarding various characteristics of their personal transportation behavior. Specifically, data indicating the individual's travel patterns, annual vehicles miles traveled, and State of residence was paired with geographically specific electricity prices (Energy Information Administration 2014a) and gasoline prices (Energy Information Administration 2014b) and fuel efficiency data for PHEVs (Silverman 2010; Department of Energy 2014) and ICVs (Cain 2014; Department of Energy 2014; Department of Transportation 2012) to determine the lifetime fuel costs for each technology.

Figure A8 in Section 6.3 of the Appendix shows a visualization of the microdata for annual vehicle miles travelled from the NHTS fit to a normal distribution, while Figure A9 does the same for current state-level gas price data. The annual vehicle miles travelled distribution shows that the majority of Americans travel less than 20,000 miles per year, with a mean of around 11,000 miles per year. Driving 11,000 miles per year is equivalent to a weekday commute of 42 round trip miles. Given that many PHEVs are designed to travel around 40 miles in electric drive, an average commuter with a PHEV will use little gasoline whether there is a vehicle charger at the place of work or not. There is obviously variability in charger locations, personal travel distances, and even PHEV electric drive efficiency, but the typical commuter driving patterns seem to align well with the operational constraints of PHEVs. The visualizations in the appendix are simplifications of the full data to aid in the visualization of the analysis, however, the results are calculated from the full dataset provided in the NHTS.

The difference between the lifetime fuel cost of ICVs and PHEVs represents the individual's economic willingness to pay for PHEVs. This data was then weighted by each State's population, and extrapolated to the set of all potential consumers in the United States (United States Census 2013), defined as the number of licensed drivers not currently incarcerated. While a driver may choose to adopt multiple vehicles at a time, this model is constructed to give each driver the choice to replace their primary vehicle with a PHEV. In order to assess willingness to pay in terms of manageable submarkets, individuals were binned into 50 cohorts of equal population and the cohorts were ordered from highest willingness to pay to lowest, as shown by Figure 16.

Market curves for this analysis were formed through the calculation of the economic willingness to pay of U.S. consumers using various levels of data resolution. This method is utilized assuming that the vehicle purchase decision is an economic one, which stands as a necessary condition of subsidy policies. Behavioral considerations, while important, have not been included in this study, although Figure A10 in the Appendix shows the potential for non-economic considerations to negatively affect PHEV adoption. Essentially, non-economic factors such as range anxiety and unfamiliarity will shrink the market for PHEVs, since many consumers will choose not to adopt a new technology even if it makes economic sense. On the other hand, certain consumers may have a desire to lower their overall emissions and choose to adopt regardless of WTP, growing the total market.

4.2.5 Cascading Diffusion and PHEV Subsidy Cost

Once individual-level willingness to pay has been calculated and individuals have been placed into bins the market curve is complete. At any given point, the difference between the experience curve and this empirical market curve represents an economically efficient subsidy level for programs intended to increase adoption of PHEVs. However, as the program proceeds and adoption increases, the curves will intersect and the experience curve will drop below the market curve, signaling economic viability of the technology, at which point the subsidy may be removed. This transition may not occur for some emerging technologies, which indicates that no subsidy program will succeed in market activation. The “free” adoption occurring through the period over which the market curve exceeds the experience curve is termed cascading diffusion, and is one indication of a successful subsidy program. This adoption will continue until full market saturation is reached, or until the curves intersect again and cost surpasses the willingness to pay of the remaining consumers.

The total cost of the subsidy program is calculated as the area between the curves over the period that the subsidy occurs: when the experience curve is greater than the market curve before cascading diffusion. The benefits of the subsidy include adoption that takes place both during the subsidy program and throughout the period of cascading diffusion, resulting in a significant improvement to societal benefit through reducing the subsidy cost per unit adopted. Following these guidelines the market situation for PHEVs is analyzed.

This mathematical formulation allows for a simple and telling quantification of subsidy program benefits. However, in reality some adoption of PHEVs will likely occur regardless of the existence of a subsidy. Ideally, only the benefits that would not have occurred without the subsidy should be attributed to the subsidy program, but this would require knowledge of the future outcome of two mutually exclusive events: the diffusion of PHEVs with and without subsidies. This information clearly does not currently exist, and no forecasts have been undertaken in this analysis. The proceeding analysis therefore follows the guidelines presented in the previous paragraph with the qualifier that it effectively stands as an upper bound to the subsidy program's total benefits.

4.3 Results and Discussion

4.3.1 Nation and State Level Cascading Diffusion Assessment

Combining the PHEV experience curves with market curves allows us to calculate the total subsidy program cost and the accompanying market potential for PHEVs in each scenario. The general trend revealed through the analysis is this: as higher resolution data are included in the analysis, the calculated benefits of a PHEV subsidy increase. The first case, which utilized nation-level data, offers a bleak outlook for any potential PHEV subsidy program. In fact, the national averages produce a willingness to pay that is below the current incompressible cost of PHEVs, meaning that no amount of subsidy or adoption will activate the market.

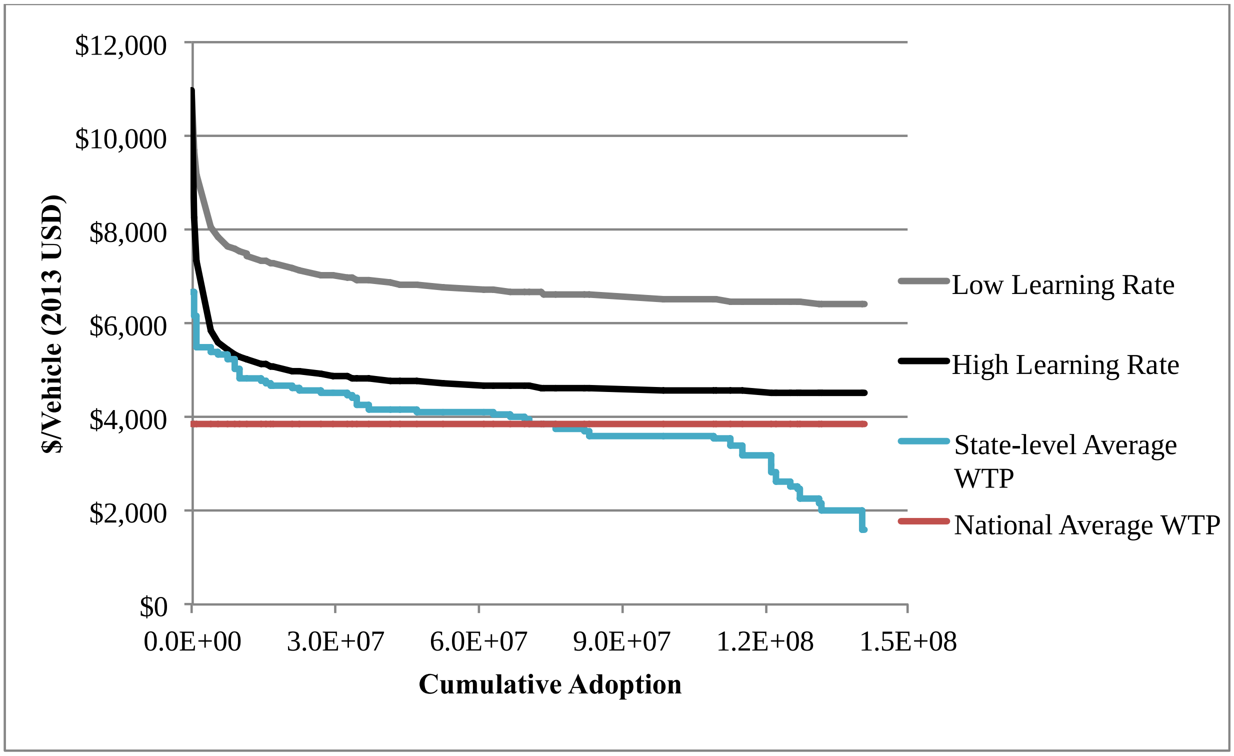


Figure 15: State- (blue) and Nation-level (red) market curves for the U.S. paired with pessimistic (gray) and optimistic (black) experience curves for PHEVs in a cascading diffusion analysis of vehicle subsidies. No crossover points exist where market curves exceed experience curves, meaning no subsidy will successfully activate the PHEV in these scenarios.

The situation is altered only slightly when the state level market curves are calculated. Based on their combination of gasoline price, electricity price, and vehicle miles traveled, the average consumers in some states are calculated to have a willingness to pay of more than double the national average. Figure 15 illustrates a change in the style of market curve from the national average, revealing 51 distinct submarkets, one for each of the states and the District of Colombia. Each submarket is as wide as the population of potential consumers in that state, and a willingness to pay corresponding to the states' average value. Table A2 in Section 6.3 of the

Appendix lists the average willingness to pay for each state in descending order, as it appears in Figure 15.

Figure 15 also shows that considering heterogeneity in state markets still reaches the same result as disregarding submarkets in the nation-level assessment. In both the nation-level and state-level analysis, the model shows that no potential subsidy program would result in any market activation, which would seem to call any attempt to incentivize adoption of PHEVs into question. However, the third and final case reverses the conclusion entirely.

4.3.2 Person Level Cascading Diffusion

The results of the cascading diffusion analysis in the third scenario are far more optimistic for a PHEV subsidy program. Including higher resolution data returns a completely different outcome. Heterogeneity of the sub-markets is magnified further when considering the willingness to pay of individual consumers, and the market curves improve and exceed the PHEV experience curves, signifying a point of market activation in figure 16. Table 9 outlines the specific results for the third case, while Figure A11 in Section 6.3 of the Appendix shows the comparison between the market curves constructed in the three scenarios. Clearly, market heterogeneity and the data resolution that allows heterogeneity to be analyzed are critical to accurately assessing the diffusion potential of PHEVs. The person-level market curve varies by 100% at times and has an average difference of over 50% as compared to the nation-level curve.

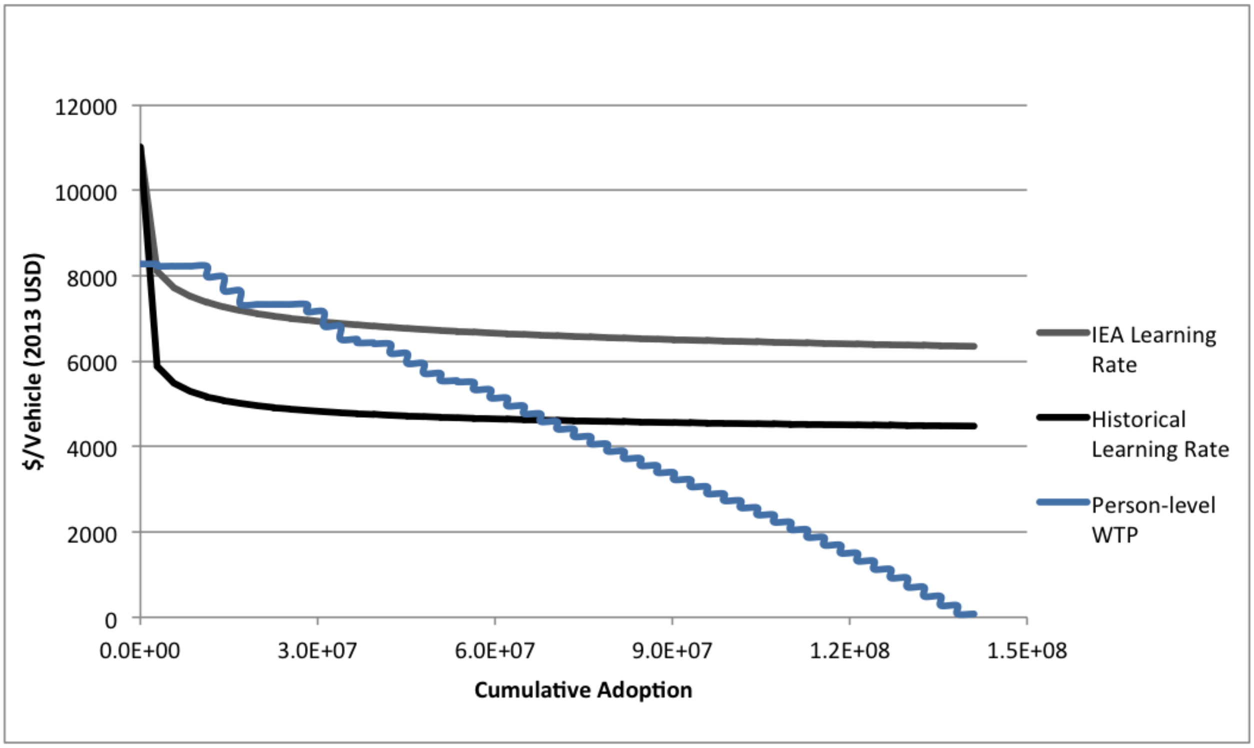


Figure 16: Person-level market curve (blue) with pessimistic (gray) and optimistic (black) experience curves for PHEVs in a cascading diffusion analysis of vehicle subsidies. In both scenarios, the person-level curve surpasses the experience curve for PHEVs, showing that short-term subsidies activate a larger market and result in the potential for robust incentive programs.

In a pessimistic learning scenario, and under current pricing conditions, a subsidy of $1.3 billion for 2.1 million PHEVs activates the diffusion of another 31 million PHEVs, resulting in an average cost per vehicle adopted of $42. In the optimistic learning rate scenario, only 220,000 PHEVs must be subsidized to activate a market of 68 million vehicles. The average cost per vehicle adopted in this case is only $3. Disregarding cascading diffusion results in average costs fifteen times higher for pessimistic learning rates, and costs are more than 300 times higher when doing the same in optimistic learning scenarios.

	Low Learning	High Learning
Total Subsidy	$1.3 Billion	$210 Million
Market Activation	2.1 Million	220,000
Cascading Diffusion	29 Million	68 Million
Cost per Vehicle	$42	$3

Table 9. Results of the cascading diffusion assessment of a plug-in hybrid electric vehicle subsidy considering person-level sub-markets

4.3.2 Net Benefits of a PHEV Subsidy

Combining the results from table 8 and the current valuation of PHEV benefits from Michalek et al. (2011) an upper bound for the net benefits of the PHEV subsidy, formulated above with equation 13, may be calculated.

$$\text{Net Benefits} = \text{Total Environmental Benefits} - \text{Total Costs} \quad (13)$$

The Total Environmental Benefits of PHEVs over ICVs is $656 per vehicle (Michalek et al. 2011), and the Total Costs of the subsidy program under current conditions are $42 per PHEV in the pessimistic case and $3 per PHEV in the optimistic scenario. With total adoption ranging from 31 million vehicles in the pessimistic case to 68 million vehicles in the optimistic case, the Net Benefits range from $19 billion to $44 billion. The fact that the results are positive indicates that the policy is in the public interest.

In addition to these benefits, a growing market for PHEVs directly influences the future viability and diffusion of all-electric vehicles (AEVs). A large market for PHEVs necessarily corresponds to an increase in the development of plug-in vehicle infrastructure, which should likely help mitigate range anxiety in AEVs due to increased charger availability. Higher PHEV adoption will also push electric vehicle batteries down the experience curve and propagate a sense of familiarity with plug-in vehicle technology. Each of these factors improves the market outlook for AEVs, and lays the groundwork for a transformation of the personal transportation industry.

4.4 Sensitivity Analysis

4.4.1 Variability in Gas Prices

To this point the analysis has focused on the present state of affairs in the US. Moving forward the viability of the PHEV subsidy is assessed at a variety of potential gas price scenarios to account for the historic volatility in gas prices. Using the same experience curves as before, the gasoline price is now allowed to vary by plus or minus $1.50, which is equivalent to considering average gasoline prices between $2.00 and $5.00 per gallon. The results are illustrated in Figure 17, and the cascading diffusion analysis is displayed in Table 10.

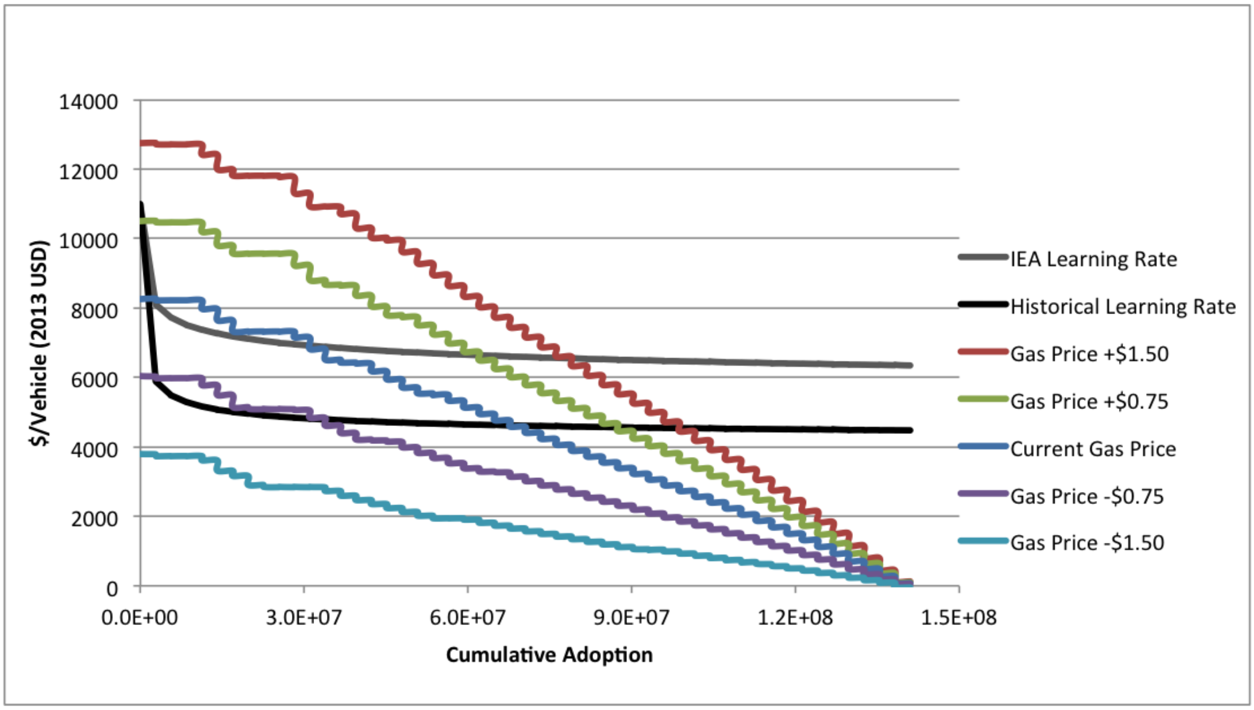


Figure 17. The effect of gas price variability on market curves for PHEVs. Higher gas prices result in higher economic willingness to pay for PHEVs relative to conventional vehicles.

Figure 17 clearly shows a strong relationship between gas price and PHEV subsidy viability. At gas prices at or above a national average of $3.50, a subsidy for PHEVs will activate a larger market and result in the total adoption of between 31 and 99 Million PHEVs. Below current gas prices, however, a PHEV subsidy is likely to fail in activating larger markets, especially in scenarios with gas prices below a national average of $2.75. In these cases, the PHEV market would rely on high learning rates to drive adoption, and a subsidy program would be unproductive.

	Low Learning				High Learning			
Gas price	**Subsidy**	**Activation**	**Total Diffusion**	**$/PHEV**	**Subsidy**	**Activation**	**Total Diffusion**	**$/PHEV**
+$1.50	0	0	7.9E+07	$0.00	0	0	9.9E+07	$0.00
+$0.75	$10 Million	4.6E+04	6.2E+07	$0.16	$3.7 Million	1.6E+04	8.7E+07	$0.04
Current	$1.3 Billion	2.1E+06	3.1E+07	$41.92	$210 Million	2.2E+05	6.8E+07	$3.04
-$0.75	-	-	-	-	$2.0 Billion	2.3E+06	3.4E+07	$58.82
-$1.50	-	-	-	-	-	-	-	-

Table 10. Cascading diffusion assessment of a PHEV subsidy at current electricity prices and various gas prices relative to current levels.

Table 10 and Figure 17 show another case in which a subsidy program would be unproductive: if gas prices increase $1.00 per gallon or more above current levels. In these scenarios, a subsidy is unnecessary to drive adoption since consumer willingness to pay for PHEVs would be so high relative to internal combustion vehicles. Improvements to the fuel efficiency of ICVs could cut into the willingness to pay values, though some of the improvements would be passed along into the hybrid engine of the PHEV. An expansion of this analysis, including an examination of the subsidy's sensitivity to electricity price, is available in the coming sections.

4.4.2 Sensitivity of Total Adoption to Electricity and Gas Prices

This section will present the results to show the model's sensitivity to both electricity prices and gas prices. Building on the information in Figure 17, a third dimension is added to the analysis and solve for the total adoption of PHEVs driven by a subsidy program given various combinations of gas and electricity prices. Figures 18 and 19 show the results for the low learning rate scenario and high learning rate scenario respectively.

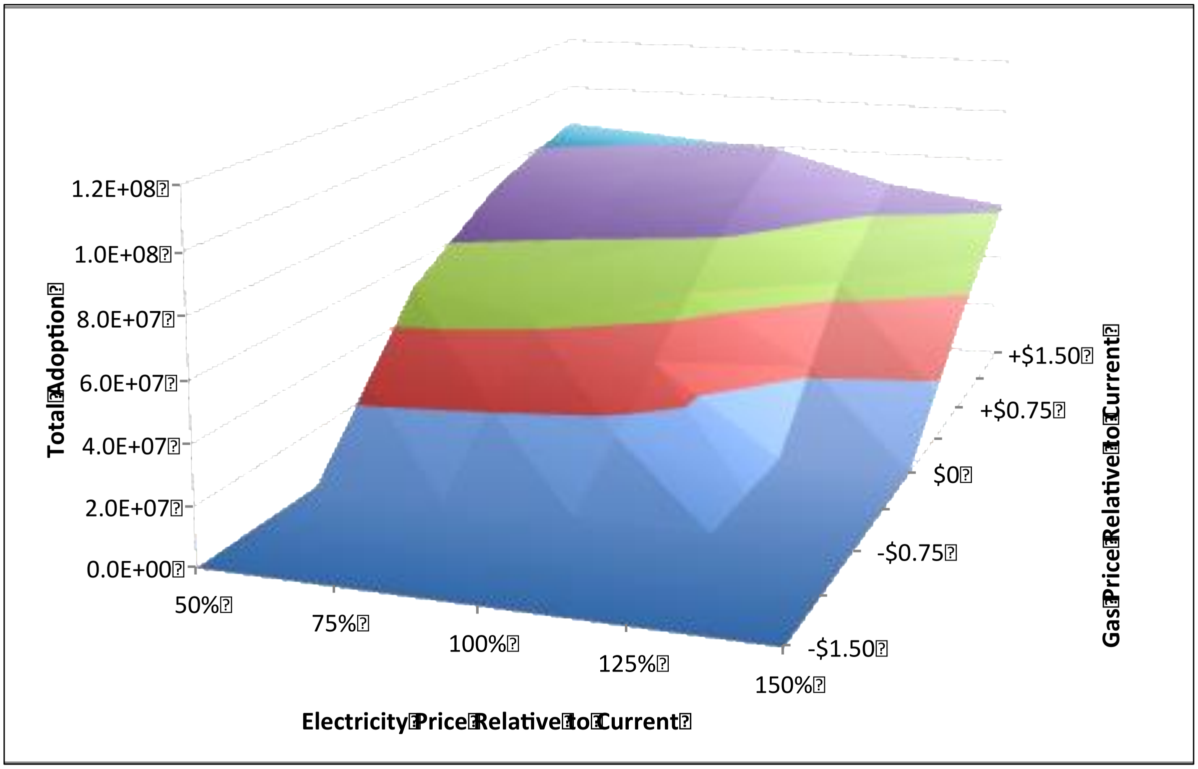


Figure 18. Sensitivity analysis of total PHEV adoption driven by a subsidy program at various electricity and gas price combinations and a low learning rate of 9.5%.

In the low learning scenario, the analysis shows that there will be no activation point, and thus no worthwhile subsidy program, for situations with gas prices below current values. On the other hand, even with high electricity prices and a low learning rate, a subsidy program could result in PHEV adoption reaching 30-60 million vehicles with high gas prices. The outlook for a subsidy program improves when considering adoption in the high learning rate scenario. There are still no successful programs at very low gas prices, equating to a national average of $2.00 per gallon, but some adoption does occur at gas prices within -$0.75 of current values. Once again the model shows a significant sensitivity to gas price, resulting in the adoption of up to 87 million PHEVs even at extremely high electricity prices.

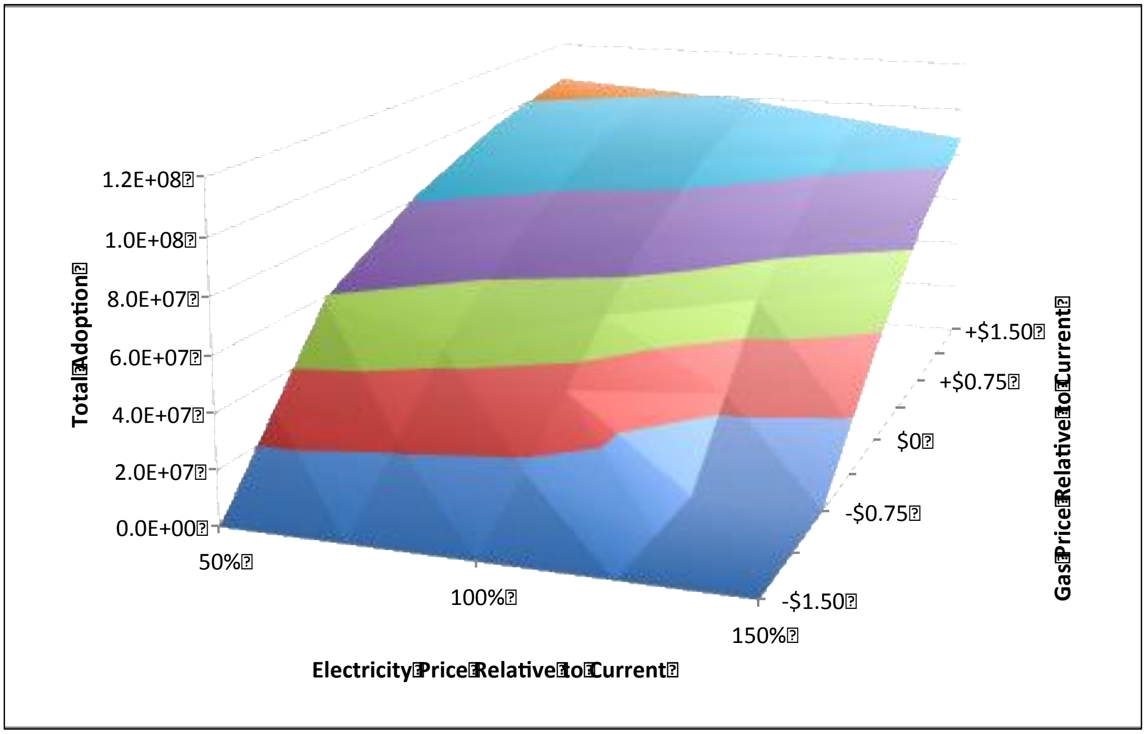


Figure 19. Sensitivity analysis of total PHEV adoption driven by a subsidy program at various electricity and gas price combinations and a high learning rate of 22%.

The most optimistic combination possible for PHEVs in this analysis is shown in Figure 19 and considers the total adoption of PHEVs at low electricity prices, high gas prices, and a high learning rate. In this case, total adoption reaches a saturation point at 91% of all potential consumers in the US. However, this result is highly unlikely for two primary reasons. First is the fact that this analysis neglects non-economic decision factors such as digging in with current ICV technology, information disconnects, and availability. These and other factors will lead to a lower value for total adoption than is projected by Figures 18 and 19. The second reason is that as PHEV adoption increases, plug-in vehicle charging infrastructure will develop in kind. While these developments can help PHEV adoption in the short-term, the availability of chargers and increased familiarity with electrified transportation may accelerate the adoption of all-electric vehicles (AEVs). Growth in PHEVs will also drive down electric vehicle battery costs, improving the cost-effectiveness of AEVs, which contain a lower incompressible cost than PHEVs due to the absence of the combustion engine. This lower incompressible cost allows the AEV experience curve to drop lower than that of the PHEV, causing it to become more attractive to a wider collection of submarkets in the long-term.

This analysis has discussed program developments in terms of relative timing (i.e. short-term vs. long term) because the PHEV market is still in the early stages of growth and plug-in vehicles account for less than a percentage point of the national vehicle fleet. The markets and subsidy programs have been assessed in terms of vehicles adopted, due to the fact that the timeline for these events is highly uncertain based on the emerging nature of the PHEV market. As the market matures, more data will become available that will decrease the significant variability in market growth rates and allow for future assessments to include a time component.

4.4.3 Sensitivity Analysis of PHEV Subsidy Net Benefits

The next step in the sensitivity analysis is to quantify the net benefits of the subsidy program with the same variety of initial conditions for learning rates, gas price, and electricity price. The net benefits were calculated according to equation 13; the difference between Total Environmental Benefits and Total Program costs. The total environmental benefits are calculated as the net benefit per PHEV, $656, taken from Michalek et al. (2011), multiplied by the total adoption attributed to the subsidy, including cascading diffusion. The total program cost is calculated by taking the area between the experience curve and the market curve up to the market activation point. Varying the input parameters within the low and high learning rate scenarios resulted in Figures 20 and 21 respectively.

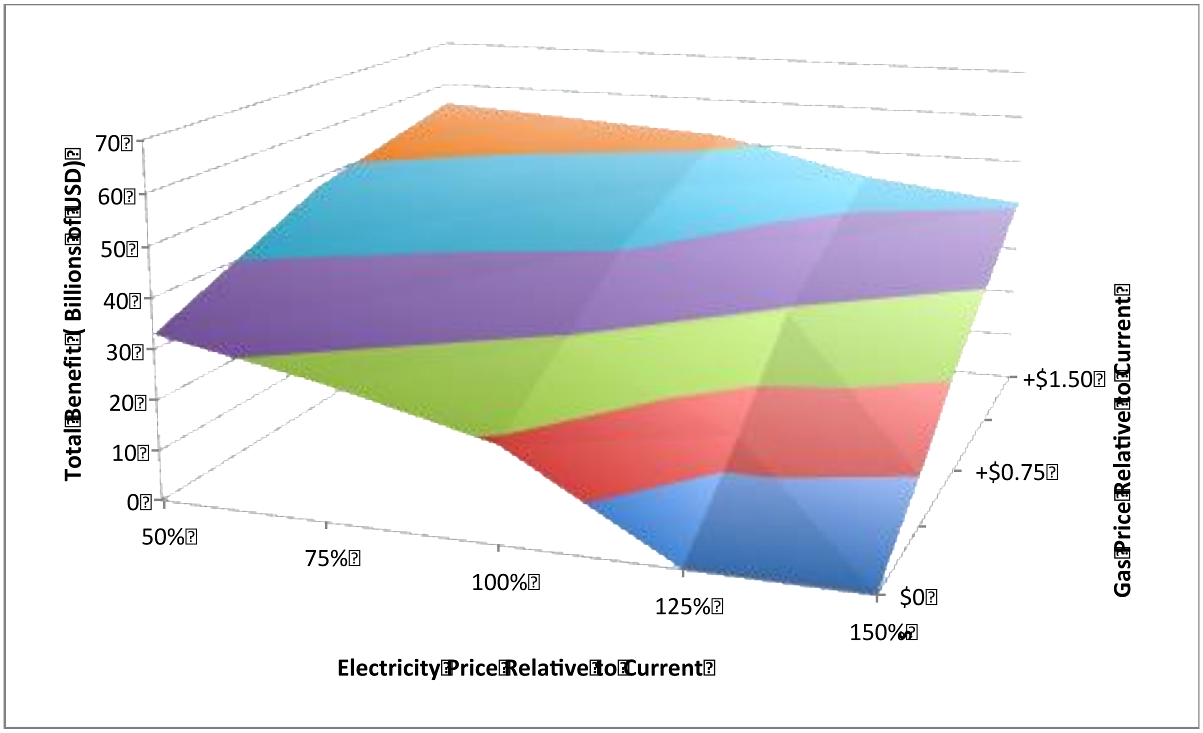


Figure 20. Sensitivity analysis of subsidy program net benefits at various electricity and gas price combinations and a low learning rate of 9.5%.

At the low learning rate of 9.5%, a subsidy program will only result in positive net benefits if gas prices stay at or above current levels. Based on Figure 18, no subsidy program is productive below current gas prices if the learning rate is low, and these results are omitted from Figure 20. However, even at low learning and current gas and electricity prices and especially in more optimistic scenarios, the model shows significant social benefits to subsidizing PHEVs. The net benefits range from $19 billion to $52 billion at current electricity costs, and from $40 billion to $55 billion if gas prices approach $5.00 per gallon.

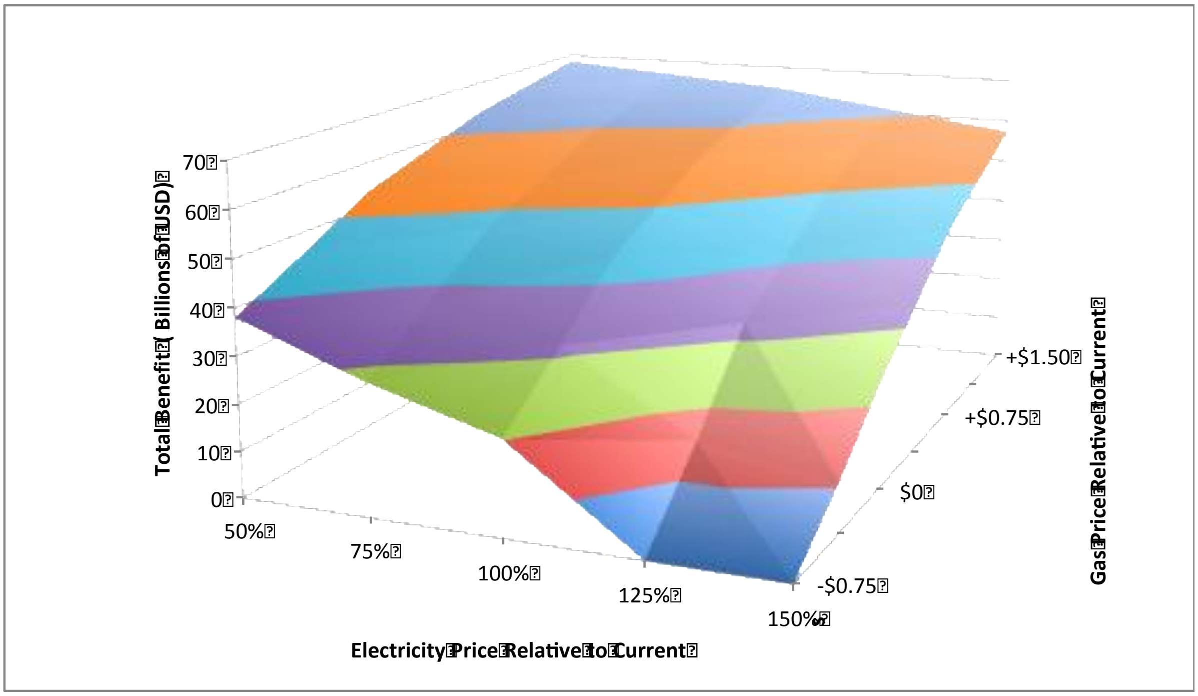


Figure 21. Sensitivity analysis of subsidy program net benefits at various electricity and gas price combinations and a high learning rate of 22%.

When examining the high learning rate scenario, a larger assortment of initial conditions are found to result in beneficial subsidy programs. For instance, even with gas prices up to $0.50 below current levels a subsidy program will result in a net benefit to society. Figure 21 clearly shows that the subsidy program benefits are more sensitive to changes in gasoline price, causing net benefits to vary from $20 billion to $65 billion at current electricity costs, while net benefits range from $23 billion to $54 billion at current gasoline prices.

4.5 Discussion and Conclusions

4.5.1 Gas Price as a Determinant of Subsidy Program Viability

Figures 17-21 have shown dependence between gasoline price and the viability of PHEV subsidy programs. This is only natural since PHEVs, as an emerging technology, are forced to compete with the incumbent ICVs in the marketplace. As gasoline prices increase ceteris paribus, the variable cost of owning ICVs increases relative to the more efficient PHEVs. However, this does not necessarily mean that additional taxation or penalties should be utilized to improve the relative economic state of PHEVs. While leveraging these mechanisms does improve the relative standing of PHEVs, they hinder the absolute economic impact of PHEVs.

A long-term solution that may help to avoid some of the short-term economic penalties of increased gasoline taxes is to increase the amount of clean renewable energy on the electricity grid. Simultaneously incentivizing the development of cleaner and more efficient energy options on the grid will increase the net social benefits accrued with each PHEV adopted by improving the environmental performance of PHEVs relative to fully gasoline-powered vehicles. In this way, both the national energy system and the transportation system may benefit from lower emissions and higher energy efficiency, and PHEVs improve both relatively and absolutely as compared to ICVs.

4.5.2 Considering Program Administration

To this point the analysis has assumed that the subsidy level at any given point is the difference between the experience curve and the market curve (i.e. the total amount of money required to make the decision economical for the given consumer). Inherent to this assumption is the fact that experience curves are calculated as continuous functions, meaning even fractional or infinitesimal increases in cumulative adoption result in reductions in technology cost. In reality, technological progress occurs in discrete segments according to improvements in materials, processes, or experience. The result of this phenomenon would be to change the experience curve into a sort of decreasing step function. The step function consideration is also more conducive to the management and administration of the subsidy program. Not only is learning unlikely to occur at such small intervals, but it is also impractical to assume that the necessary data will be available on a continuous basis to administer the subsidy as quantified above.

To assess the impact that the assumption of continuous learning has on the model the net benefits of a fixed subsidy program are considered. Under this type of policy, the subsidy is set at the initial cost gap and stays at the fixed amount until market activation is projected to occur according to the technology’s progress down the experience curve, at which point the subsidy is removed. Figure 22 illustrates this program style and represents the upper bound for the program cost, because the fixed subsidy essentially overpays all but the first, or first few, cohorts. However, the stability of this policy style is beneficial to producers, since they are able to plan budgets and production around the fixed subsidy.

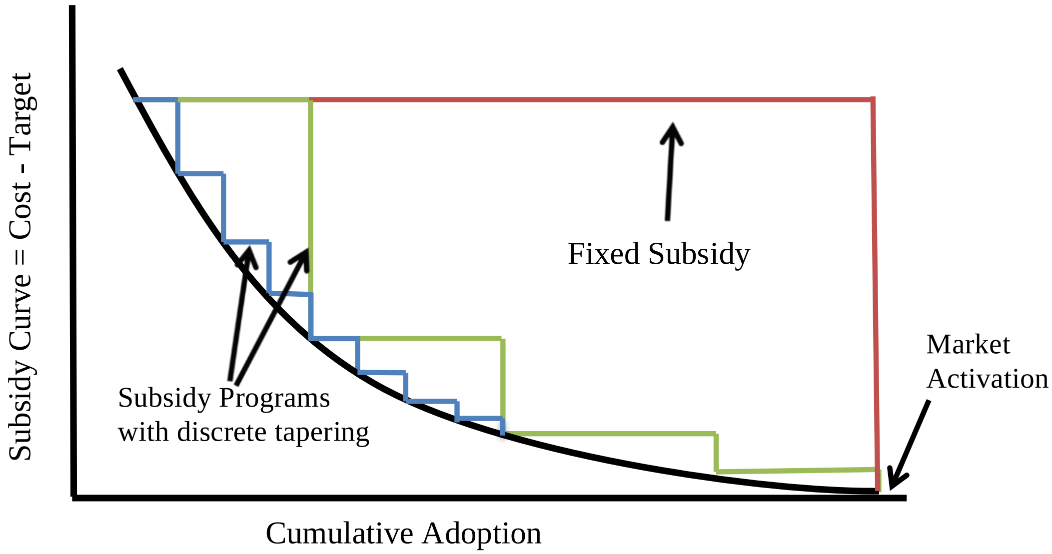


Figure 22. A comparison of a continuous subsidy function (black), subsidy programs that taper at discrete intervals (blue and green), and a fixed subsidy program (red). The area under each curve represents the total cost of the subsidy program.

Stability in program administration can result in the benefits mentioned above, though a tapered subsidy that is dependent on technological progress may have benefits as well. For example, regular reductions in the subsidy amount per vehicle may incentivize early adoption as consumers race to receive higher subsidies. Tapered subsidies also save significant amounts of public funds, as shown by Figure 22. This multi-criteria decision process should be dealt with on a case-by-case basis, and must begin by incorporating technological progress assessments into the policymaking process.

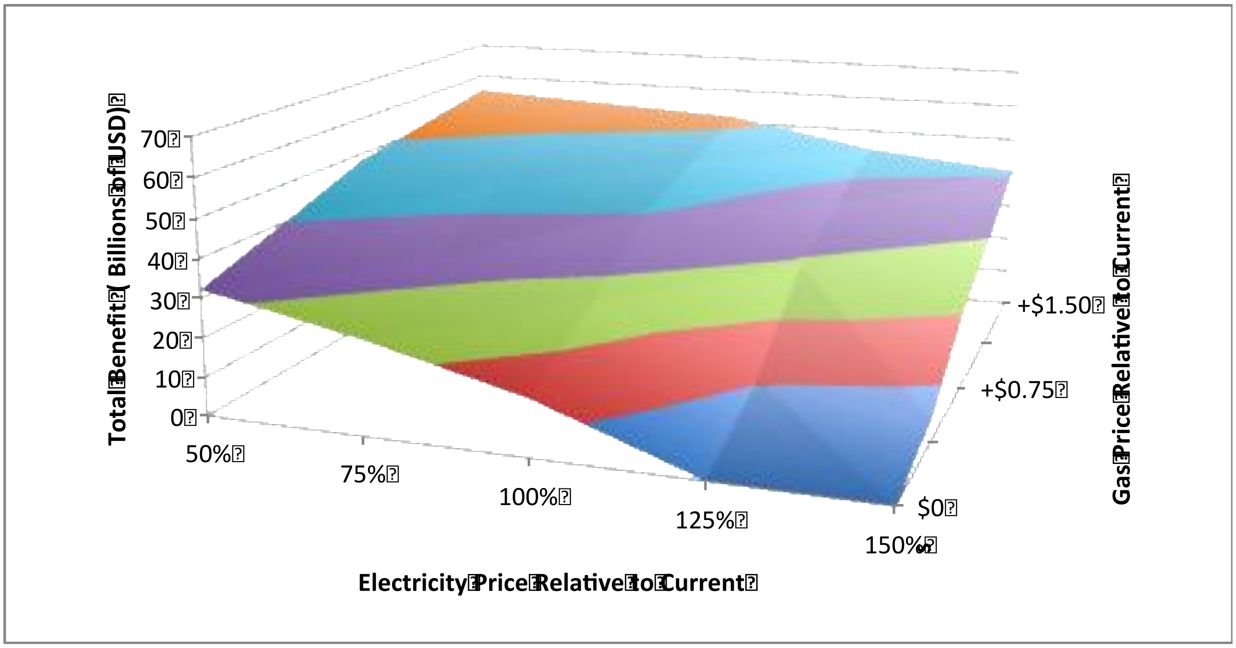


Figure 23. Sensitivity analysis of a fixed subsidy program's net benefits at various electricity and gas price combinations and a low learning rate of 9.5%.

Figure 23 quantifies the net benefits of a fixed subsidy program in the low learning rate scenario. Fixing the price of the subsidy increases program costs and reduces net benefits, but still results in positive net social impacts over the same combination of initial conditions, since the subsidy is still removed at the market activation point and experiences the same amount of cascading diffusion as in the previous scenarios. The reduction in total economic benefits is more drastic at lower gas prices, since more funds are required to make PHEVs viable in these scenarios. At high gas prices, corresponding to national averages over $4.50, there is no impact on program benefits since no financial incentives are necessary for PHEVs in these cases. Using a fixed subsidy model as opposed to an iterative model shown by Figure 20 reduces the total program benefits by an average of 8%.

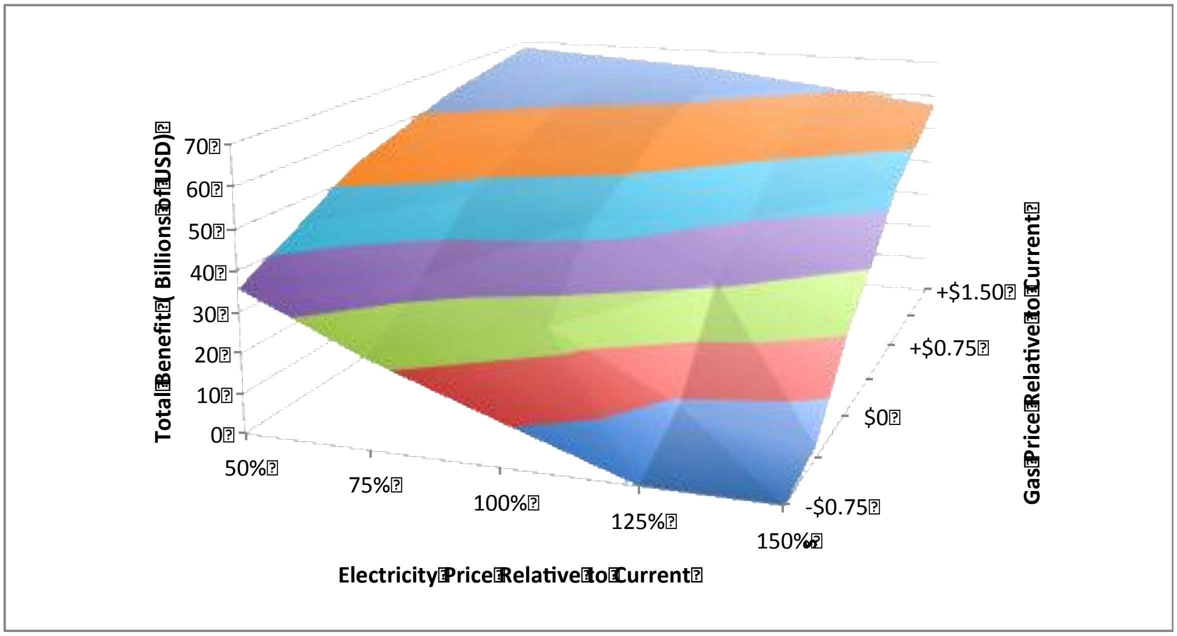


Figure 24. Sensitivity analysis of a fixed subsidy program's net benefits at various electricity and gas price combinations and a low learning rate of 22%.

At the high learning rate, the average reduction in total program benefits increases to 10% relative to previous scenarios. This value is higher than in the low learning rate fixed subsidy scenario because the reduction in technology costs, and correspondingly the reduction in subsidy required, occurs at a faster rate, which increases the distance between the fixed subsidy and continuous subsidy curves. This means that the fixed subsidy will overpay by more in the high learning rate scenario than in the low. Figure 24 shows the full results of this analysis for an array of initial conditions.

4.5.3 Conclusions

Technological progress and the consideration of learning rates are essential to the formation of more beneficial and lower cost subsidy programs. Continuously tracking the progress of a technology over the life of a subsidy program could save billions of dollars in public funds and allow governments to identify market activation and saturation points in order to take advantage of cascading diffusion. Incorporating learning rates at a smaller scale by predicting market activation in fixed subsidy programs can result in savings as well, while driving adoption of a socially beneficial technology. From an administrative standpoint, structures must be put in place in policymaking organizations and organizations involved in policy analysis to assess technological progress of emerging technologies. These considerations could save public funds in current policy programs, and could also be a key determinant in whether or not to subsidize an emerging technology in future programs.

V. Conclusions

5.1 Discussion of Uncertainty in This Research

A range of uncertainty considerations accompanies the quantitative modeling presented in this dissertation. The three primary types of uncertainty that exist within this research are scenario, model, and parameter uncertainties. Scenario uncertainty pertains to the assumed scope that is analyzed in each chapter and how inputs are presumed to be related. For example, in Chapter 3, the future cost of lead and other battery materials is a source of scenario uncertainty. Figure 13 assumes an asymptotic cost for lithium-ion and lead-acid batteries using current materials pricing. The model could be altered to reflect some long-term growth in materials prices since prices will likely increase over time, however, the purpose of the Figure is to provide a lower bound on the experience curves, and since current costs are likely to be lower than future material costs, this scenario uncertainty was acceptable. This was also the case with gas prices in Chapter 4. While the analysis bounds gas prices between average costs of $2-$5 per gallon, gas prices outside this bounding could still exist, in which case the model would necessarily have to change the scenarios being considered.

The largest scenario uncertainty in this dissertation is the fact that each Chapter quantifies only the economic basis for energy policy decision-making. While important behavioral aspects do exist, this research has been prepared under the assumption that government incentive programs must first and foremost, if not only, satisfy the necessary economic conditions for consumer choice. Whether behavioral considerations are to be dealt with by the government is a matter of debate, but regardless of the entity in charge of considering consumer behavior, this information is critical to the success of future programs and should be incorporated in government decision-making.

Model uncertainty arises in the choice of which quantitative methods to utilize in an analysis. This dissertation has relied solely on a single factor experience curve for ease of calculation and because this model satisfies Ockham's razor; it is the simplest model that still performs well enough to complete a robust analysis. If the scope of this dissertation was to solely develop the most realistic experience curve for a technology, a new approach utilizing multi-factor experience curves may have been chosen. In that case, the model would be able to account for uncertainties in technological progress that exists outside of the learning rate, such as major advances in research and development. If a major advance were to happen in a technology discussed in this research, such as a discovery that reduces lithium-ion battery costs by 50%, the current single-factor model would simply have to alter the input parameter for initial cost of the technology, and repeat the calculation of the experience curve from that new starting point. A multi-factor model may be able to incorporate these advances into the modeling structure, so that the analysis would not have to start over to reflect the new conditions.

Another example of model uncertainty exists in the assumption in this dissertation that the government would want to cash in on externality benefits alone by utilizing a least-cost model for subsidy program development like those presented in Chapters 2, 3, and 4. If, for example, the government's goal was to replace all gas vehicles with EVs as soon as possible, then they could potentially give EVs away to replace all registered vehicles. In that case, the analysis presented in Chapter 4, and particularly Figures 15, 16, and 17 would have to be altered so that the x-axis value for cumulative adoption increased from 150 million to nearly 300 million, so that the model assessed total vehicles replaced, rather than licensed drivers who have chosen to adopt PHEVs.

The final type of uncertainty in this research is the most commonly discussed form, which is parameter uncertainty. As with most quantitative assessments using secondary data, the values used throughout this dissertation have been found in the literature and utilized in the models and scenarios presented previously. In some cases, such as the learning rate for lithium-ion batteries in Chapter 2, or gas prices and PHEV learning rates in Chapter 4, bounds have been used to account for uncertainty and variability in the input parameters. In other cases, a best value has been found from a trusted source and utilized as-is so that the analysis may proceed. While this may introduce some uncertainty into the analysis, the author argues that the value of the quantitative and qualitative results is far greater than the cost of introducing incremental uncertainties to certain portions of the analysis.

5.2 Summary and Key Points

This dissertation has presented three new methods, each with a case study, in the field of technological progress. The key finding in this project has been the importance of considering technological progress and learning rates throughout the policymaking process. In each case, utilizing technological progress assessments as a primary component of subsidy policies for energy technologies has the potential to save billions of dollars in public investment, while enabling the coordination of efficient incentives for socially beneficial technologies. The specific contributions made by each chapter are outlined below.

Chapter II developed a model for creating learning-dependent tapered subsidy programs for emerging technologies. The tapering was assessed at various intervals to show the difference in total program costs at alternate tapering schedules. Using a range of learning rate inputs, the sensitivity of net public investment to learning rate was also tested using the first publicly available experience curve constructed for lithium-ion batteries. The results showed that when developing learning-dependent subsidy programs, the tapering interval must be chosen carefully in the interest of cost savings and administrative practicality. The fact that total program cost is highly dependent on the technology's learning rate is also a key result, implying that learning rates must be considered in the policymaking process.

Chapter III introduces the idea of residual learning rates, which represent the learning experienced by a technology when materials costs have been disaggregated from a technology's experience curve. The residual learning rates allow us to assess progress in a technology, in this case lead-acid batteries, despite volatile materials cost data. Learning in lead-acid batteries is particularly important, as the batteries currently represent the incumbent technology in the arena of both small automotive and large backup power battery systems. The construction of an experience curve for lead-acid batteries allowed for a gap to parity analysis of lithium-ion batteries, showing that the existence of learning in an incumbent technology, which essentially results in a moving cost target, can drastically effect the total time and investment required for an emerging technology to reach parity. Since many emerging technologies qualify for subsidies or other financial incentives, consideration of learning rates in existing technologies is also important within the policymaking process to ensure efficient allocation of public funds.

Chapter IV outlines the methods required to assess fractional, heterogeneous markets for energy technologies. By examining data on the individual consumer level, market curves can be constructed based on each consumer's willingness to pay for the technology. The use of high-resolution data also revealed that the assessment of energy policies, and specifically subsidies, is highly dependent on the level of resolution in the input data (i.e. consumer level versus state or nation level). This chapter also distinguishes the purpose of a subsidy into distinct segments, concluding that the diffusion of a socially beneficial technology is the primary goal and is therefore the necessary determinant when setting subsidy levels. When applied to a case study of PHEVs, the result is a robust cascading diffusion assessment of PHEV subsidy policy.

5.3 The Path Forward for Sustainability Research

Each chapter provides new insights for the utilization of technological progress models for energy technology policies. The methods outlined above are presented through specific case studies, although they may also be applied to a range of technologies and situations. By furthering the use of technological progress modeling in subsidy policies, more efficient policies may be constructed for technologies in order to accelerate progress up the diffusion s-curve and improve overall sustainability. More specifically, the benefit of technological progress modeling is that it not only informs a necessary condition of economic viability of government programs, but the accompanying learning rate values and scenario analyses lead to clear go/no-go recommendations for decision-makers.

To increase the potential impact of technological progress modeling, learning rate studies and experience curves must become central components of the policymaking process. These models help inform the benefit-cost assessments of government energy programs, and allow researchers to move away from traditional retrospective policy analysis towards prospective policy analysis and development. This process would allow better, more economical program to be developed for emerging energy technologies. To make this process a reality, increased collaboration at the research-government-industry nexus must be encouraged to ensure researchers have the best available data to provide decision-makers with the valuable tools they need to design the next generation of energy policies. While this represents only one piece of sustainable development for the energy industry, promoting sustainable technologies will have a key role in a future sustainable energy system.

VI. Appendices

6.1 Appendix to Chapter II

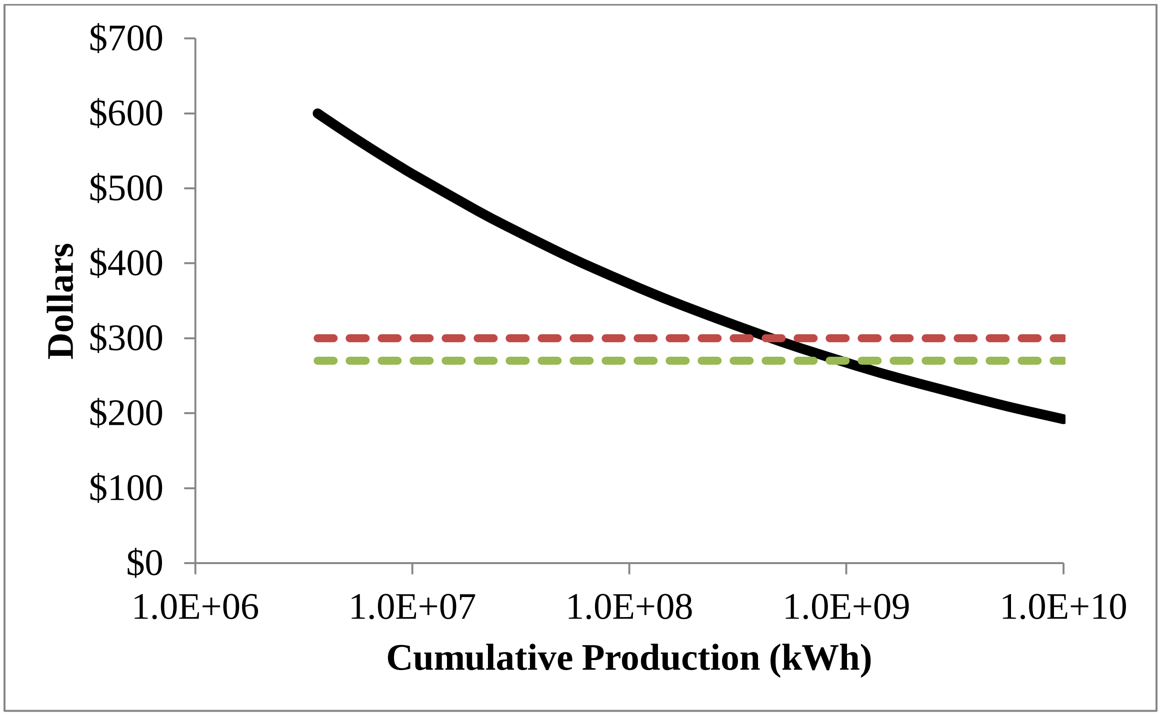


Figure A1. The experience curve (black) and cost target for lithium-ion electric vehicle batteries, where the cost target is $300/kWh (red) and $270/kWh (green) and the learning rate is 9.5%.

The experience curve minus the cost target line in Figure A1 would produce the red subsidy curve found in Figure A2. When the cost target is $300, lithium-ion batteries reach the target after 450 GWh of cumulative production and just $5 billion of total public investment. When the target is moved down, the technology must experience deeper cost reductions, 950 GWh of production, and receive $20 billion extra in subsidies to reach the crossover point.

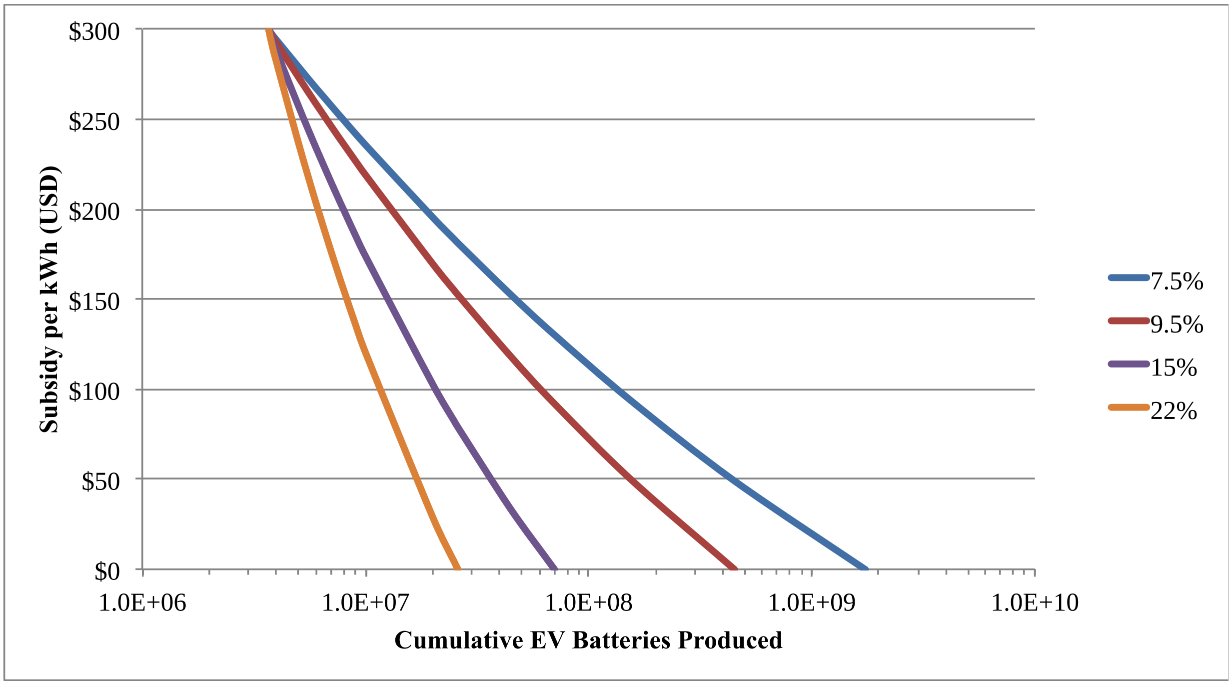


Figure A2. Subsidy required per kWh as cumulative production increases at various learning rates.

Price reductions, and therefore subsidy requirements, occur far more rapidly at higher learning rates. Following the subsidy curve is equivalent to assuming a continuous taper for a subsidy program. The area under each curve represents the total cost of the subsidy program.

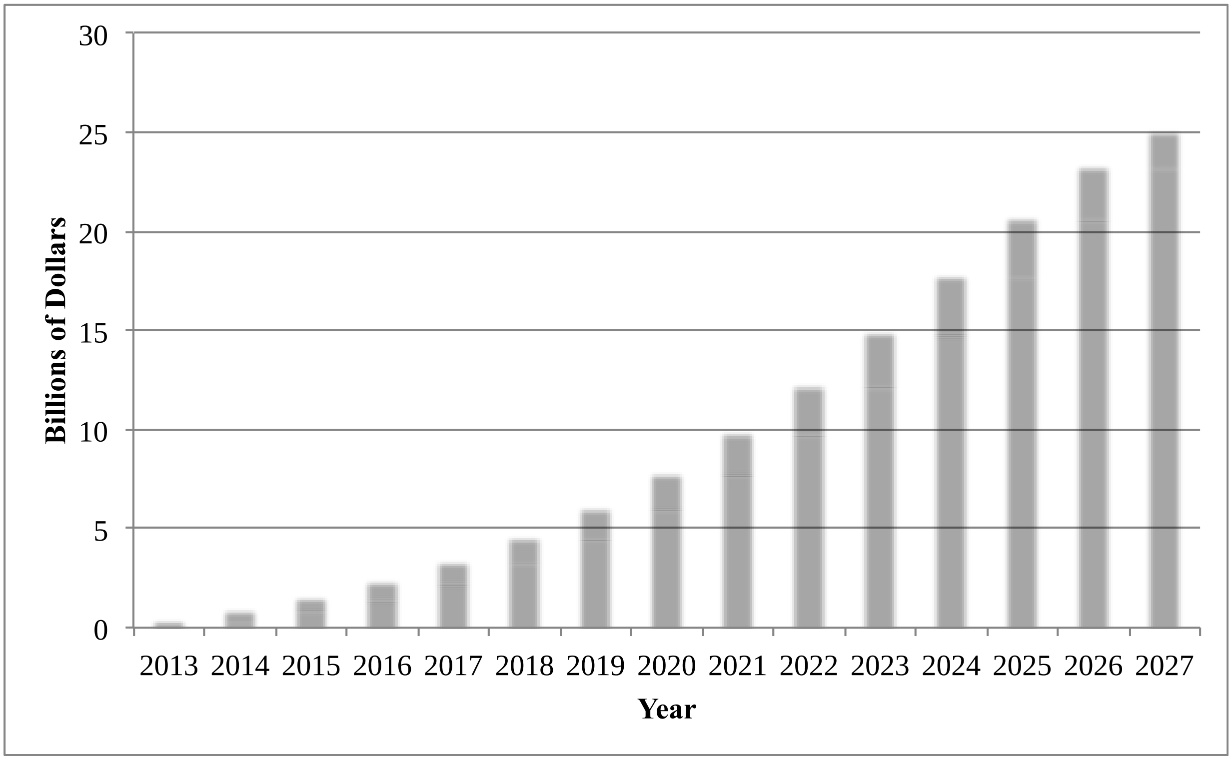


Figure A3. Annual (blue) and cumulative (red plus blue) investment for a subsidy program tapered annually over a 15-year timeline given a 9.5% learning rate.

Figure A3 shows that a longer timeline on the subsidy program due to lower growth rates in electric vehicle production can actually help reduce total program costs by allowing more annual tapers than in the 10-year timeline shown in Figure 6. This result may be slightly better for policymakers, though expanding the timeline by 5 years pushes the potential environmental benefits of higher adoption out into the future. These benefits must then be discounted, which may negate any potential savings in the subsidy program. Extending program timelines may hurt growth rates, which defeats the purpose of attempting to speed adoption and market growth through financial incentives.

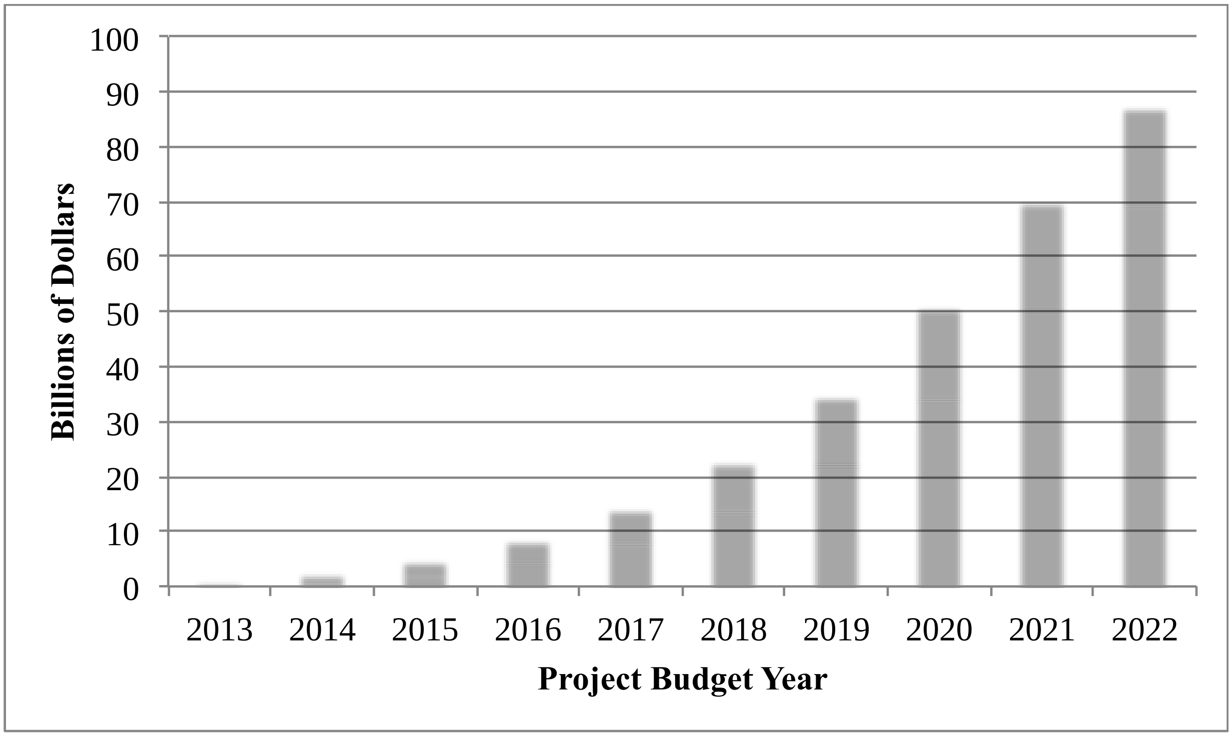


Figure A4. Annual (blue) and cumulative (red plus blue) investment for a subsidy program tapered annually over a 10-year timeline given a 7.5% learning rate.

Reducing the learning rate for lithium-ion batteries over the same 10-year time frame drastically increases total program costs, resulting in a more than tripling of total cost. This is due to the higher growth rates required to bring electric vehicle costs down the experience curve, which results in a higher adoption level required, and therefore a higher total amount of subsidies.

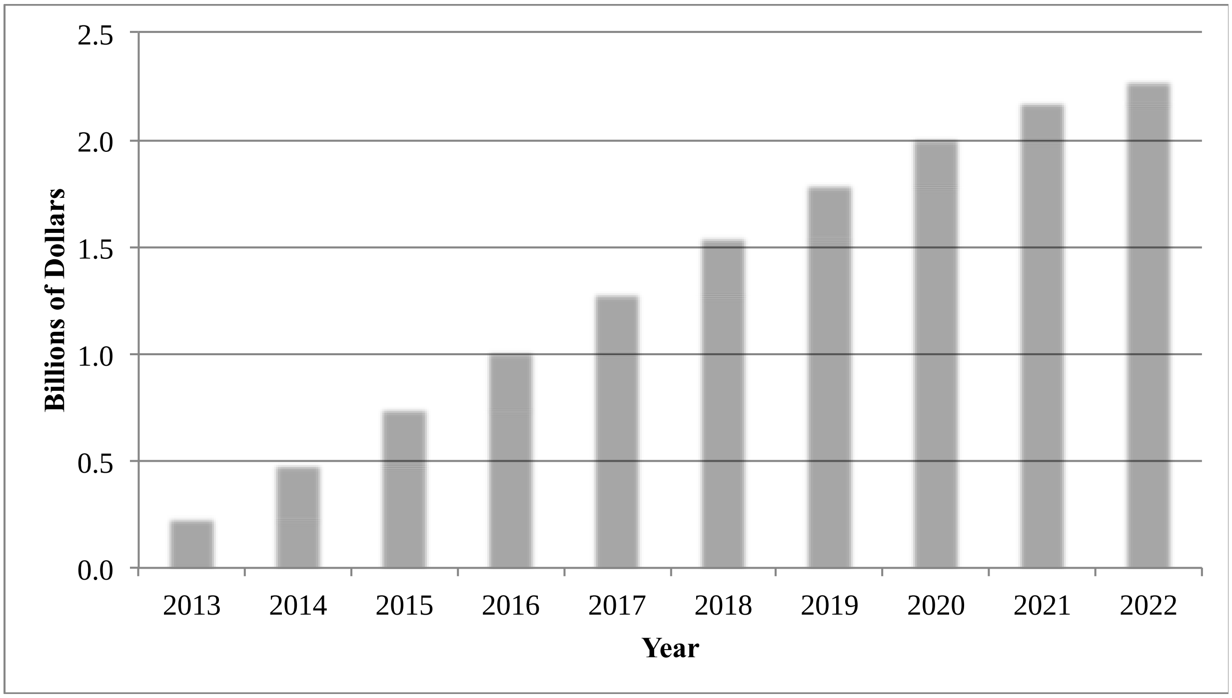


Figure A5. Annual (blue) and cumulative (red plus blue) investment for a subsidy program tapered annually over a 10-year timeline given a 22% learning rate.

Using a higher learning rate, 2.3 times that in Figure 6, results in a 90% reduction in total program costs. In this case, far fewer electric vehicles must be purchased to reach the cost target, meaning fewer vehicles are subsidized, and total program costs are greatly reduced.

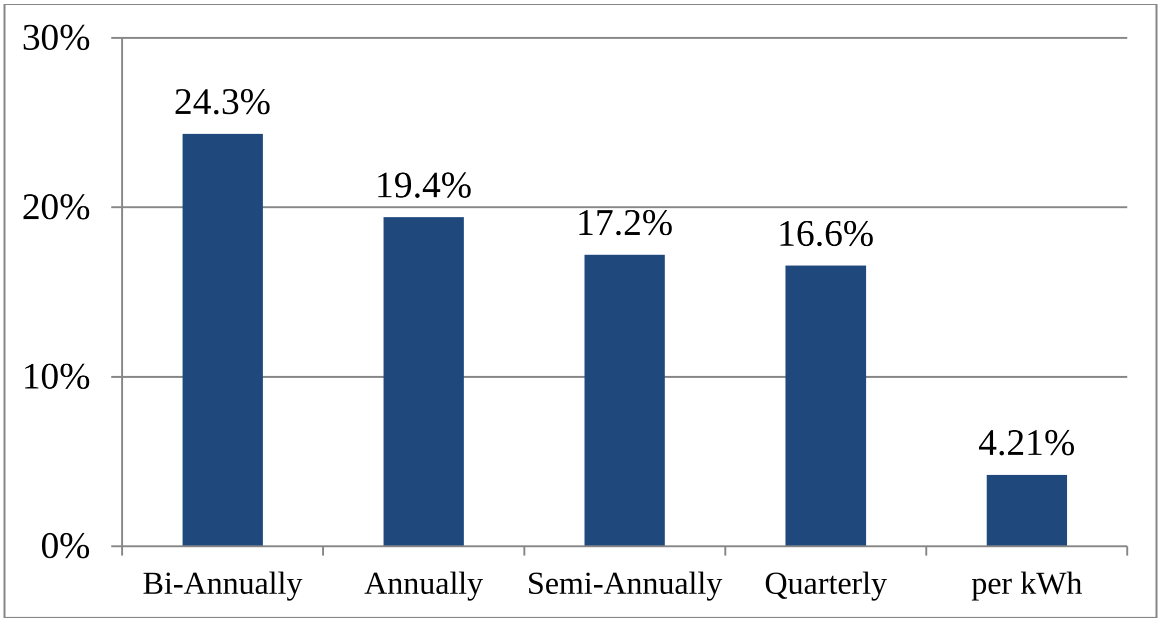


Figure A6. Percentage of total investment in electric vehicles provided by the government subsidy program.

As the subsidy program is tapered more frequently, two changes take place. First, and as previously illustrated in Figure 4, the total cost of the subsidy program decreases. The second change that occurs is that the total fraction of the investment in the technology provided by the government program decreases. This is because a more frequent taper reduces the amount of cases in which the program overpays the consumer(s). A higher frequency taper therefore results in an emerging technology becoming less dependence on public funds to succeed in the marketplace.

6.2 Appendix to Chapter III

Year	Small	Large
1984	100	100
1985	100	100
1986	98	99
1987	103	100
1988	114	116
1989	108	120
1990	110	121
1991	110	125
1992	107	121
1993	103	123
1994	100	118
1995	105	123
1996	111	114
1997	112	117
1998	110	116
1999	109	115
2000	110	129
2001	111	127
2002	111	136
2003	111	134
2004	112	131
2005	120	137
2006	123	149
2007	135	159
2008	179	224
2009	174	214
2010	182	201
2011	185	216
2012	192	222

Table A1. Producer Price Index (PPI) values for small and large lead-acid batteries according to (Producer Price Index 2013; Producer Price Index 2014).

6.3 Appendix to Chapter IV

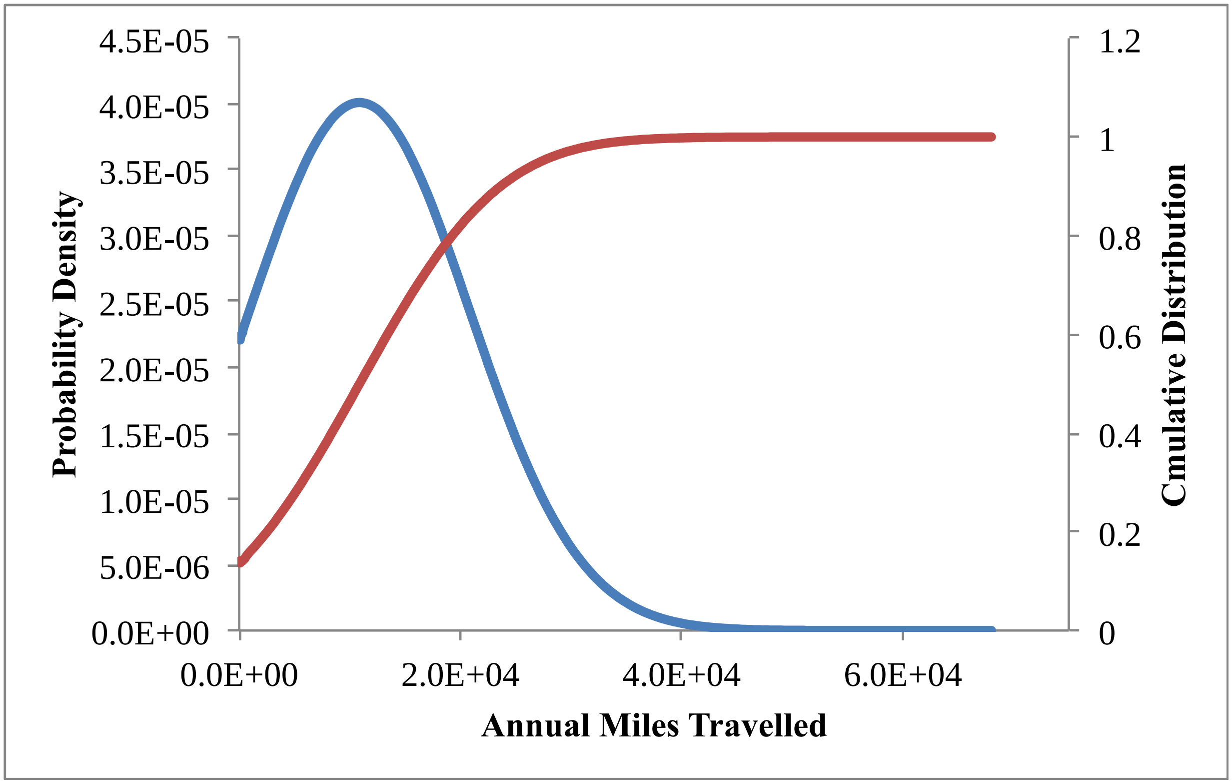


Figure A7. Annual vehicle miles travelled microdata from the National Household Transportation Survey ("National Household Transportation Survey" 2011) fit to a normal distribution.

Figure A7 shows that 80% of individuals drive less than 20,000 miles per year. Those individuals driving over 20,000 miles per year will be unlikely to purchase a PHEV, since they drive an equivalent of nearly 80 miles per work-day, requiring them to use significant amounts of gasoline even after having paid a premium for a PHEV. Individuals driving less than 5,000 miles per year will also be unlikely to adopt PHEVs, since they do not spend enough on gasoline to incentivize the adoption of a more efficient vehicle.

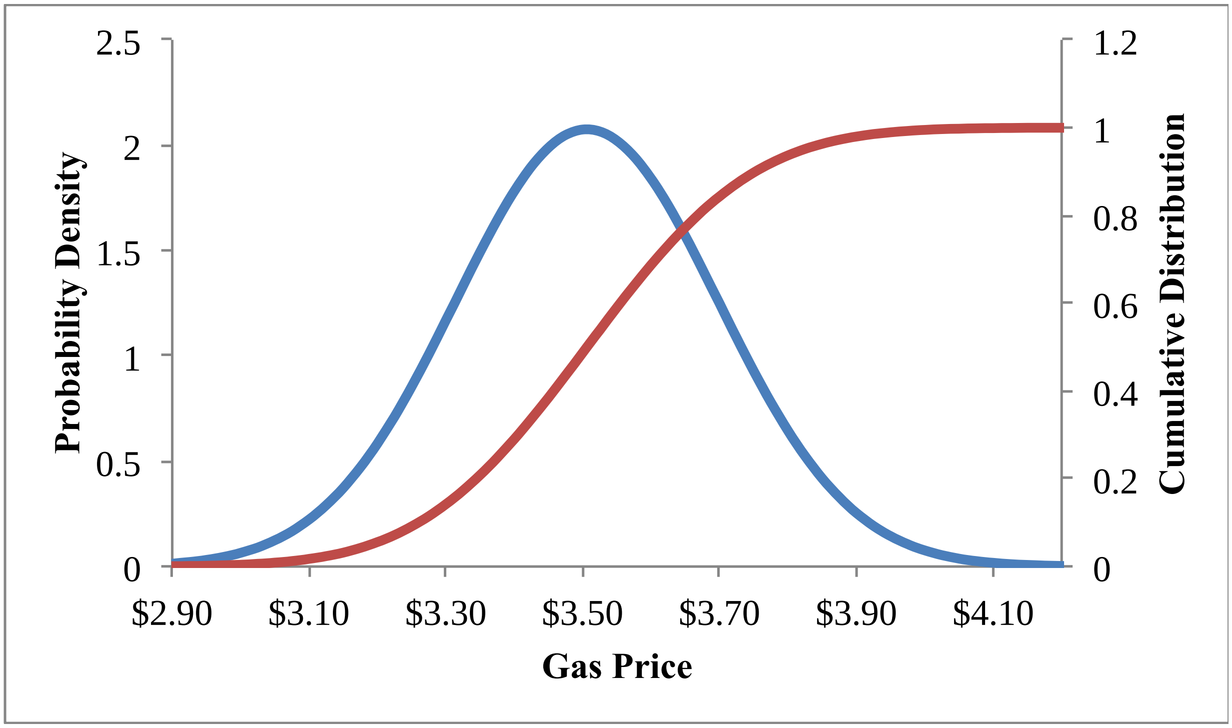


Figure A8. State-level gas price data (Energy Information Administration 2014b) fit to a normal distribution

The gas price distribution shows the average price of gasoline in the US to be $3.50. Some states experience gas prices above $3.50 and therefore, ceteris paribus, consumers in those states have a higher willingness to pay for PHEVs, due to the reduction in gasoline expenditures.

State	Willingness to Pay	State	Willingness to Pay
WY	6694	OR	4094
ND	6168	VA	4075
IN	5488	WI	3993
OK	5383	VT	3991
KY	5337	UT	3951
MS	5252	AL	3850
NM	5027	ME	3843
AR	4836	CO	3843
SD	4832	IL	3730
MO	4818	NV	3718
WV	4756	CA	3615
NE	4736	TX	3598
MT	4674	DE	3573
GA	4669	AZ	3525
IA	4638	MD	3418
NC	4566	PA	3179
MN	4527	AK	2986
TN	4501	NH	2848
ID	4454	MA	2611
KS	4405	CT	2518
LA	4276	RI	2450
MI	4167	NJ	2289
SC	4161	DC	2156
WA	4143	NY	2017
OH	4128	HI	1594
FL	4125		

Table A2. State-level willingness to pay accounting for heterogeneity in gas price, electricity price, and annual vehicle miles travelled.

Table A2 shows that accounting for submarkets and increasing data resolution drastically affects the results for consumer economic willingness to pay. Now 42 States have an average willingness to pay above the national average.

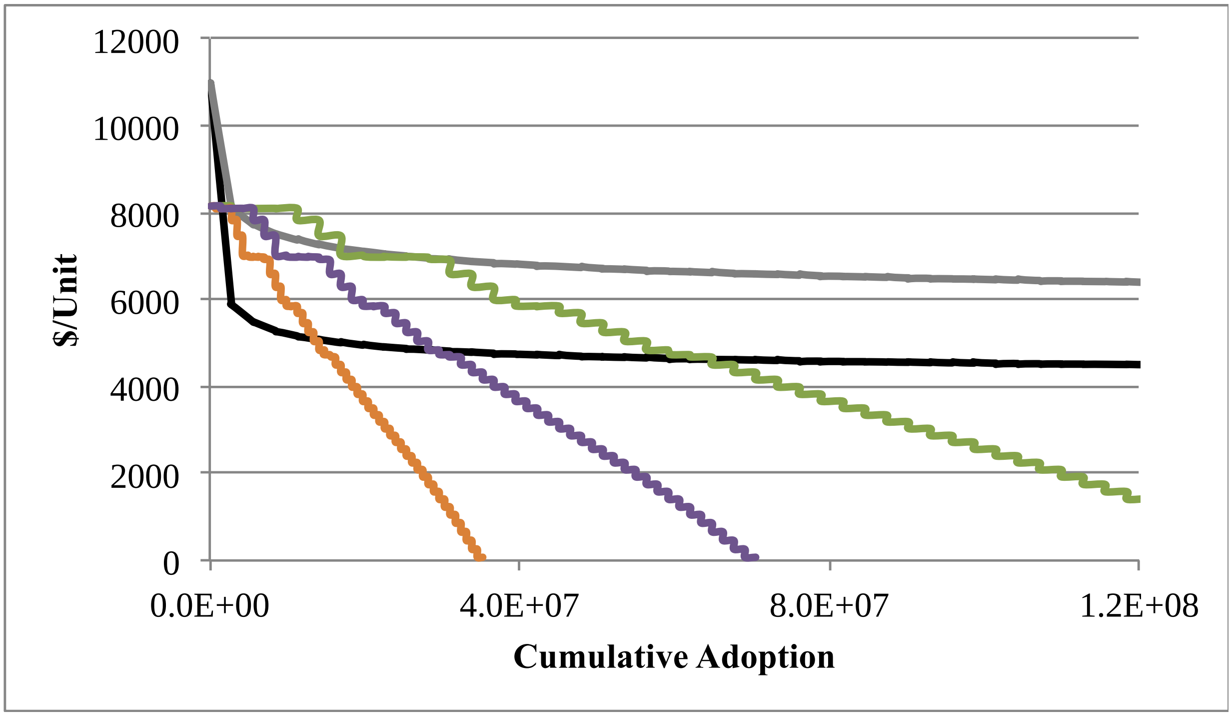


Figure A9. The potential effect of introducing non-economic constraints into the PHEV market curve. The green line shows the original curve while the purple and orange curve represent market curves with 50% and 75% of consumers being removed for non-economic reasons, respectively.

Figure A9 shows that removing a percentage of consumers from the market due to non-economic constraints will decrease the size of each submarket, resulting in a sort of clockwise rotation of the market curve. Reducing the potential consumer base by a high proportion could eliminate market activation and any cascading diffusion for PHEVs, as shown by the fact that the orange market curve no longer intersects the gray experience curve. A more complex way to assess non-economic consideration would be to study the implicit discount rates used by individual consumers. This method would also shift the market curve down if consumers were resistant to the new technology.

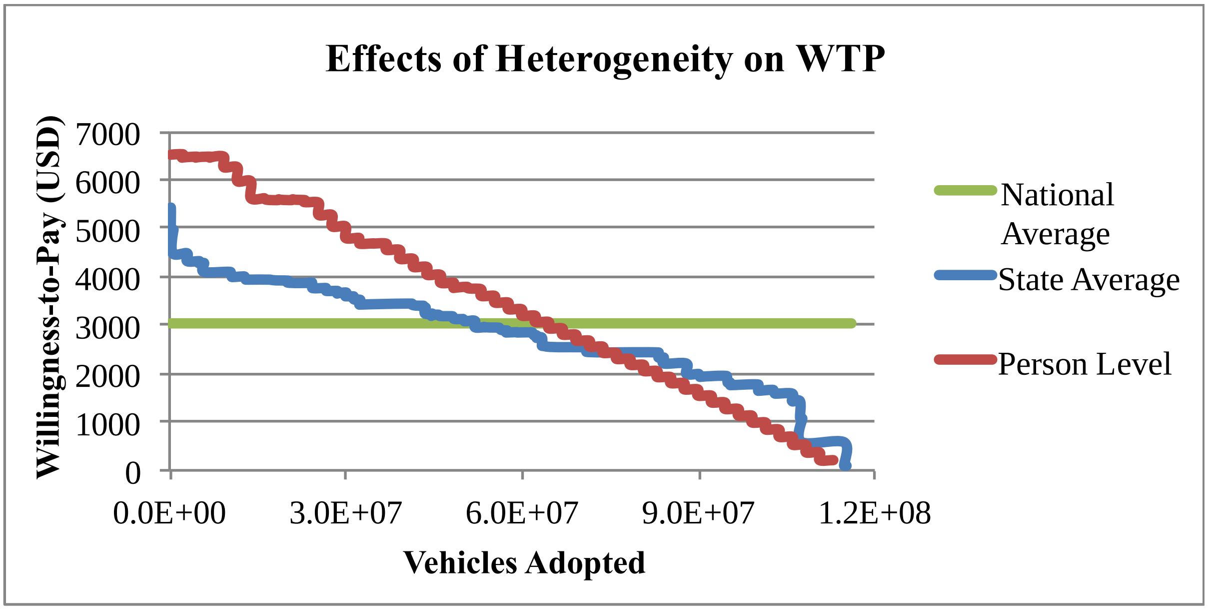


Figure A10. Variation in market curves for plug-in hybrid electric vehicle based on differences in data resolution.

Analyzing the economic willingness to pay for PHEVs of different consumers requires the use of higher resolution data to account for heterogeneity in the market. Figures A7 and A8 clearly show a wide variety of initial conditions for individual consumers that are neglected by a national average, or state average assessment of PHEV market potential.

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