How Uncertain is the Future of Electric Vehicle Market: Results from Monte Carlo Simulations Using a Nested Logit Model

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ABSTRACT

Plug-in electric vehicles (PEVs) are widely regarded as an important component of the technology portfolio designed to accomplish policy goals in sustainability and energy security. However, the market acceptance of PEVs in the future remains largely uncertain from today's perspective. By integrating a consumer choice model based on nested multinomial logit and Monte Carlo Simulation, this study analyzes the uncertainty of PEV market penetration using Monte Carlo simulation. Results suggest that the future market for PEVs is highly uncertain and there is a substantial risk of low penetration in the early and mid-term market. Top factors contributing to market share variability are price sensitivities, energy cost, range limitation and charging availability. The results also illustrate the potential effect of public policies in promoting PEVs through investment in battery technology and infrastructure deployment. Continued improvement of battery technologies and deployment of charging infrastructure alone do not necessarily reduce the spread of market share distributions, but may shift distributions toward right, i.e., increase the probability of having great market success.

Key Words: energy transition, electric vehicles, market penetration, charging infrastructure, Monte Carlo simulation, consumer choice

1 INTRODUCTION

Achieving a sustainable transportation future implies a transition from petroleum-based, internal combustion engine (ICE) vehicles to ones powered by alternative fuels (NRC, 2013; Greene et al., 2013; GEA, 2012). Plug-in electric vehicles (PEVs), including plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEVs), received much attention in recent years. Since the introduction of Nissan Leaf and Chevrolet Volt in December, 2010, the cumulative sales of PEVs in the United States exceed 160,000. Announced by President Obama in March 2012, *EV Everywhere* initiative aims “to produce PEVs as affordable and convenient for the American family as gasoline-powered vehicles by 2022” (U.S.DOE, 2013). China, Japan, and Europe also set targets and launched major initiatives for promoting PEVs. For example, China has set ambitious targets of having 5 million PEVs on the road by 2020. Central and local governments are offering generous subsidies to PEV purchase, sales tax exemption, and even experimenting free license plate in certain cities, which could be very expensive (e.g. $12000 a license plate in Shanghai). However, the success of PEVs needs to overcome major barriers, such as high vehicle price, BEV's limited range and long charging time, consumers’ aversion to the risk of new technologies, and the availability of charging infrastructure. Furthermore, there is substantial uncertainty in technology progress, consumer preferences, and infrastructure deployment. Therefore, the market penetration of PEVs is highly uncertain from today’s perspective.

Improved understanding of the uncertainty is needed to inform public policy making. The objective of this paper is to quantify the uncertainty of PEV market penetration by Monte Carlo simulation. More specifically, the paper tries to answer the following questions:

1. What is the approximate distribution of PEV market shares in future years?
2. What are key factors that contribute to the variability of PEV penetration?

Answering these questions has important policy implications. Enhanced understanding of future PEV market uncertainty helps estimate environmental and energy benefits of PEVs. Identifying important factors helps make better policies by allocating limited resources effectively to key areas.

Few work in the literature studied the uncertainty of alternative fuel-powered vehicle market penetration. Greene et al. (2013) and Lin et al. (2013) investigated the sensitivity of hydrogen fuel cell vehicles to technology progress, infrastructure availability, and consumer preferences. However, the two studies didn't perform comprehensive uncertainty analysis. This paper is among the first that examines the uncertainty of PEV penetration by combining a consumer choice model with Monte Carlo simulation. With the help of the @Risk software (Palisade Corp.), this paper uses Monte Carlo simulation to understand the magnitude and contributing factors of PEV market uncertainty.

2 APPROACH

The basic approach in this study is Monte Carlo simulation using the Market Acceptance of Advanced Automotive Technologies (MA3T) model and @Risk. The MA3T (Lin, 2012) is an Excel-based market simulation model that estimates market shares of various vehicle technologies from 2010 to 2050. @Risk is a commercial software package that performs risk analysis using Monte Carlo simulation to show many possible outcomes in a spreadsheet model and probability of each outcome. The first step is to select a set of model parameters and specify their probability distributions. Then at each simulation, @Risk will sample the set of parameters and call MA3T to estimate vehicle market shares. Summary statistics can be extracted after the simulation, such as probability distributions of market shares and tornado graphs showing key factors determining market outcomes.

One approach for forecasting the market penetration of alternative fuel powered vehicles is based on Bass diffusion theory (Bass, 1969, 2014). Example studies include Becker et al. (2009) and Mabit and Fosgerau (2011). The major limitation of this approach is the lack of the connections between many influence factors and market share. Another more popular approach is to use discrete choice models. Transportation economists have estimated various discrete choice models using stated and/or revealed survey data. For example, Brownstone et al. (1996) estimated a multinomial logit model (MNL) using California stated survey data with the choice set of gasoline and electric vehicles. Later Brownstone and co-authors (2000) estimated a MNL and a mixed logit model using both revealed and stated survey data. Ito et al. (2013) estimated a nested multinomial logit (NMNL) model for Japan market using stated survey and the choice set includes gasoline, hybrid, electric, and fuel cell vehicles. These econometrics models typically do not intend to make predictions and the focus is to understand the relationships between variables.

Prediction models are designed to forecast long term penetration level of alternative fuel vehicles in response to changes in technology, policies, and market conditions. An early pioneer in this area is Transition toward Alternative Fuel Vehicles: TAFV (Greene,2001). The model is built upon the foundation of discrete choice theory while also incorporating transition dynamics. As an illustration, the model specifically captures manufacturers' learning by doing and scale economy effects and results manufacturing cost reduction as vehicle sales increase. Other similar models include LAVE-Trans (Greene and Liu,2013) and EMOB (Gosh et al.,2011). EMOB also considers the interaction between car market and other related industry sectors. The MA3T model is a further development of TAFV with the most notable improvement in market segmentation. The details of MA3T model can be found in the report (Lin and Greene, 2010). The following section provides a brief overview of the model so that readers can better understand simulation results.

2.1 THE MA3T MODEL

Developed by Oak Ridge National Laboratory (ORNL) for the U.S. Department of Energy, the MA3T is a nested multinomial logit (NMNL) model that estimates future market shares of 17 powertrain technologies, separately for passenger cars and light trucks.

2.1.1 Nested Structure and Model Equations

The technology set includes conventional gasoline and diesel vehicles, hybrid, plug-in hybrid, battery electric, and fuel cell vehicles. These technology choices are nested according to the structure in Figure 1. Technology abbreviations are explained in Table 2. At the top of the structure is the choice of buying a new light-duty vehicle (LDV) or not. Under the buying nest is the choice between a passenger car and a light-duty (LD) truck. Within each vehicle type consumers choose among different powertrain technologies, grouped into three classes: (1) conventional/HEV, (2) hydrogen, and (3) battery-electric vehicles. Within the conventional /HEV class, technologies are grouped into conventional internal combustion engines (Spark Ignition Conv, Compression Ignition Conv, and Natural Gas Conv), hybrid electric vehicles[1] (SI

[1] Note that hybrid electric vehicles are not really electric vehicles, as they are powered by liquid fuels and cannot plug into off-board sources of electricity. The battery on board is charged by regenerative braking and the internal combustion engine. The energy from the battery can provide extra power to the vehicle during acceleration. Thus,

HEV,CI HEV, and NG HEV), and SI PHEVs. SI PHEVs come in three types according to their on-board electricity storage capacity and electric motor power: SI PHEV10, SI PHEV20, and SI PHEV40. Within the Hydrogen class, technologies are grouped into Hydrogen internal combustion engines, fuel cell HEV, and fuel cell plug-in HEV (FC PHEV10, FC PHEV20, FC PHEV40).

The probability that a consumer will choose technology i, given a choice among the vehicles in nest jkl, is given by the following equation.

$$p_{i|jkl} = \frac{e^{\beta_{jkl} \cdot c_{ijkl}}}{\sum_h e^{\beta_{jkl} \cdot c_{hjkl}}} \quad \textbf{(1)}$$

In equation 1, c_{ijkl} is the generalized cost, or utility value in present value dollars of technology i in nest jkl. The parameter β_{jkl} determines the sensitivity of technology choices in nest jkl to their generalized cost. Each technology's generalized cost is comprised of a weighted sum of functions of the values of its attributes. Let the z^{th} attribute's value be represented by x_{zijkl} , its function be $f_z(x_{zijkl})$, and its weight w_{zjkl} . The generalized cost for choice ijkl is given by equation 2.

$$c_{ijkl} = \sum_z w_{zjkl} f_z\left(x_{zijkl}\right) \quad \textbf{(1)}$$

At present the following attributes are included in the generalized cost function.

- vehicle retail price
- fuel and electricity cost

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the name of "hybrid electric vehicle" does not accurately reflect the technology nature of the vehicle. It is used in this paper to be consistent with common usage.

- battery replacement cost
- range
- home backup power
- refueling and recharging accessibility cost
- make/model availability
- technology risk
- policies
- purchase subsidy, tax credit, HOV access, free parking, etc

Generalized costs of the choices within a lower nest are “averaged” and passed up to the next level.

$$c_{jkl} = \frac{1}{\beta_{jkl}} \cdot \ln\left(\sum_i e^{\beta_{jkl} \cdot c_{ijkl}}\right) \qquad \textbf{(1)}$$

The choice among nests at the next level is a logit function of their generalized costs, c_{jkl} , and price sensitivity at the next level, represented by β_{kl}. The unconditional choice probability for technology i in nest jkl, is the product of the conditional choice probabilities.

$$p_{ijkl} = p_{i|jkl}\, p_{j|kl}\, p_{k|l}\, p_l \qquad \textbf{(1)}$$

The model parameters, price sensitivity and the value consumers attach to vehicles’ attributes, are not estimated from a single survey, but calibrated to the best available evidences in the literature (e.g. available revealed preference and stated preference surveys and sales data). A detailed review of the literature evidences and the calibration can be found in the report (Greene and Liu,2012). This is consistent with the “synthetic utility function” approach promoted by

Massiani (2012), which argues analyses relying on a single survey are at risk of bearing the bias of the survey method and the promoted approach allows for more robust market penetration analysis and policy recommendation.

Alternative specific constants in the model are calibrated to currently available vehicle sales data in the U.S. (e.g., PEV data is available from 2011 to 2014). Alternative specific constants (ASCs) in the model are calibrated to currently available vehicle sales data in the U.S. (e.g., PEV data is available from 2011 to 2014). Note that ASCs reflect the mean of unobserved attributes. ASCs will be large negative numbers if a consumer choice model fails to include those factors which are barriers to PEV penetration, such as lack of charging availability/range anxiety, less make and model diversity, and risk aversion for novel technologies. The model may generate misleading results when forecasting PEV market penetration because those non-technology factors will be changing as the market evolves (Massiani,2014). Remedying this issue makes it necessary to use a modeling framework which not only captures those important non-technology factors in the utility function but also formulates the evolution of these factors as functions of the market conditions. The MA3T model is developed according to this principle. In particular, it includes feedback loops, where non-technology factors influence next year sales which in turn change non-technology factors one year after. The details of the feedback mechanism can be found in the references (NRC,2013; Greene et al.,2013).

ASCs for PEVs in the future years are assumed to converge toward conventional vehicles, reflecting our belief that unobserved attributes of PEVs may eventually be similar to those of conventional vehicles. A reviewer points out this assumption is discussible as some attributes of

PEVs remain a handicap net of attributes already accounted for in the utility function. We acknowledge the disagreement and note that our assumption is made for modeling convenience and it is just one plausible scenario for the future market development.

The model's short-term prediction accuracy is validated by backcasting and comparing with actual market shares. The validation error is small.

2.1.2 Market Segmentation

MA3T includes a detailed segmentation of the motor vehicle market to better represent systematic heterogeneity in consumer demand. Each market segment is a different "representative consumer" with distinct attributes and preferences. The targeted U.S. light-duty vehicle consumers are divided into 1,458 segments based on 6 dimensions: census divisions, residential areas, attitudes toward novel technologies, driving patterns, home recharging situations, and work recharging situations (Table 1). Within each of nine Census regions light-duty vehicle sales are divided among urban, suburban and rural areas. Within each area sales are further subdivided according to consumers' attitudes to the risk of novel technologies, using the three basic groups of diffusion theory (Rogers, 1962): early adopters, early majority, and late majority. Within each risk group, there are three levels of intensity of vehicle usage, described by daily driving distributions. The daily driving distributions have important implications for the functionality of limited range of BEVs and for the shares of electricity and gasoline use by PHEVs (Lin and Greene, 2011a). The market is further split according to the availability of charging facility.

2.1.3 Model Input and Output

MA3T takes input of technology attributes, consumer preferences, infrastructure availability, energy prices, and policies and estimates choice probabilities of each vehicle technology for each market segment.

The choice probabilities are then used to calculate market shares, vehicle sales and stock, petroleum use, and greenhouse gas (GHG) emissions. Some of the outputs serve as feedback signals and affect the purchase probabilities in the next year. For example, vehicle stock at year t affects vehicle price at year $t+1$ through the manufacturer learning by doing, and affects consumers' risk preference for the technology at year $t+1$ as well; vehicle sales at year t affects make/model diversity of the technology at year $t+1$.

The input to MA3T is from various sources. Vehicle technology attributes are taken from the Argonne National Laboratory's (ANL's) Autonomie model (http://www.autonomie.net/). The baseline values of vehicle prices are listed in Table 3.

Energy prices are from Annual Energy Outlook (AEO) published by the U.S. Energy Information Administration (EIA). The size of each consumer segment is estimated using census data and surveys. These inputs are relatively reliable for short term market prediction but subject to substantial uncertainty for mid and long term predictions. Therefore it is useful to perform uncertainty analysis using Monte Carlo simulation.

2.2 Simulation Settings

Before conducting Monte Carlo Simulation, @Risk requests users to specify probability distributions for parameters which will be sampled in the simulation. According to their potential importance in impacting market outcomes, we have selected 19 model parameters, which can be grouped into energy prices, technology, market behavior and consumer preference, and infrastructure availability. Their probability distributions are summarized in Table 4. Parameters are assumed to follow uniform distribution if no additional information is available to fit parameters to other distributions. The definition of each parameter is explained in the sections titled Energy Prices, Technology, Market Behavior and Consumer Preferences, and Infrastructure Availability.

2.2.1 Energy Prices

Gasoline and diesel prices directly determine fuel cost of ICE vehicles and they are subject to deep uncertainty in the future. The baseline gasoline/diesel prices are from AEO 2012 Reference Case (U.S.DOE/EIA, 2012). In the simulation, these prices are varied by ±50%, as controlled by gasoline and diesel price multiplier (#1 in Table 4), which is assumed to follow triangular distribution and range from 0.5 to 1.5.

2.2.2 Technology

High Battery cost is a major barrier to PEV penetration. The baseline values of battery cost ($/kwh) is taken from Autonomie (Figure 2). The progress of battery cost reduction can be varied in the simulation, either accelerated or delayed up to five years (#2 in Table 4).

MA3T simulates learning by doing effect of vehicle manufacturing, i.e., vehicle cost declines as more vehicles are produced and manufacturers learn from the production experience. The manufacturer learning rate determines the “progress ratio”, which describes the effect of doubling cumulative production on vehicle price. Despite the substantial empirical evidence for learning effect there is no theory that can be used to predict the learning rate or progress ratio for a new product. Instead, researchers often base their assumptions on historical experience with similar production processes. While historical data provides useful reference points, this method of selecting a learning rate is ultimately an educated guess. The default learning rate is 6.114e-6, corresponding to a progress ratio of 0.96. The default learning rate is assumed to vary by ±50% in the simulation (#3 in Table 4).

2.2.3 Market Behavior and Consumer Preferences

There is a great deal of uncertainty about how the market will respond to alternative vehicles and fuels over the next several decades. The uncertainty is simulated along the following lines: (1) the sensitivity of car buyers’ choices to price, (2) PEV make and model diversity, (3) the value of time, (4) the perceived cost of range assurance for BEVs, and (5) how will the market value the risk and innovativeness of advanced technologies.

Car buyers’ sensitivity to price is of central importance to the market success of advanced technologies. Higher price sensitivity implies that consumers will switch from one alternative to another for even a small change in value. A lower sensitivity implies that even apparently inferior products will attract some buyers. In the simulation, price sensitivity (# 4 in Table 4) varies by ±50% relative to the baseline assumption in MA3T.

Compared with conventional vehicles, PEVs have less make and model diversity and thus may lose attractiveness to some car buyers. Two model parameters are relevant: market provision of PEV makes and models (#5 in Table 4) and the value of make and model diversity to consumers (#6 in Table 4). Both values vary by ±50% in the simulation.

Refueling convenience is particularly important for vehicles with limited refueling infrastructure (e.g., fuel cell vehicles). MA3T quantifies the cost of refueling inconvenience by estimating the additional detour time on road in order to refuel. Thus refueling cost is a function of refueling infrastructure availability, consumer value of time, and vehicle range. The MA3T default value of time (#7 in Table 4) is $20/hour and it varies by ±50% in the simulation.

Major barriers to BEV market penetration are its limited range and long recharging time, which implies that the BEV may not be usable on days when a driver's travel distance exceeds the vehicle's range. In the MA3T model, the cost of this limitation is represented by a fixed charge for each day the BEV's range is less than the desired daily driving distance (based on empirically estimated daily vehicle travel distributions). The fixed charge per day should be in line with the cost of different options: cancelling the trips, substitution for a gasoline vehicle in the household, substitution for a rental car, and switching to other transportation modes. Depending on the household's preferences and other characteristics (e.g., the availability of a gasoline vehicle in the household), the cost perceived by consumers are expected to vary widely. The baseline value (#8 in Table 4) is varied by ±50% in the simulation.

Because of the large differences in energy efficiency among drive train technologies, the cost of energy valued by consumer could be an important factor in choices among technologies. The default assumption of the MA3T model is that consumers will consider 5 years of future fuel costs discounted to present value at 7% per year. This is consistent with assumptions used in the Department of Transportation/National Highway Transportation Safety Administration fuel economy rulemaking (U.S.EPA/DOT, 2012). However, the economic literature reflects widely differing interpretations of consumers' willingness to pay for fuel economy (Greene, 2010). Thus the simulation varies perceived vehicle life (#9 in Table 4) in the range of 2.5 to 7.5 years, following a triangular distribution. For BEVs, perceived vehicle life is also related to how consumers estimate range assurance cost. The impact of perceived vehicle life on BEV share is a mixed effect: the longer perceived vehicle life, the larger perceived energy cost savings but the bigger range assurance cost.

How the market values the risk and innovativeness of advanced technologies is another area that is largely unknown yet important to purchase decisions. MA3T segments the market into early adopters, early majority, and late majority. But very little is known about the percentage of each group. MA3T default is 10%, 37% and 53% respectively. The simulation varies the percentage of early adopters (#10 in Table 4) in the range of 5% to 15% while partitioning the remaining market in such a way that the ratio of early majority and later majority is always 0.37/0.53. It is assumed that early adopters are willing to pay (WTP) for innovativeness of advanced technologies and by contrast, early and late majority are averse to the risk of them. WTP and risk aversion cost decline as more vehicles are on road. Cumulative sales at which WTP/risk aversion is reduced by ½ control the decline rate. Both WTP/risk aversion cost and decline rate (#11 - #16 in Table 4) will vary by ±50% in the simulation.

2.2.4 Infrastructure Availability

Charging infrastructure can be described by location (home, workplace, and public) and charging speed (Level 1, 2, and DC fast charging[2]). Level 1 charging uses a standard 110 volt, 15-20 usable ampere circuit. Level 1 recharging is slow, taking more than 20 hours to fully charge a Nissan Leaf. Level 2 charging uses a 220 volt, 40 ampere circuit and requires much shorter charge time. With Level 2 charging, a full recharge requires less than 4 hours for a Nissan Leaf. DC fast charging uses a 440 volt, three-phase circuit, typically providing 60-150 kW of off-board charging power. DC fast charging may not be necessary at home or even workplace where vehicle parking duration is normally long, but would be very useful in public places like shopping mall or along highways.

Home recharging is probably the most important because home is where vehicles park most often and longest and charging at home adds little hassle to drivers (Lin and Greene, 2011b). Workplace and public charging extends the electric range and thus enables more energy cost savings for PHEVs and improves feasibility of BEV operation (Dong et al., 2014; Dong and Lin, 2012). Based on several sources (Lin and Greene, 2010; Kurani et al., 2009; Axsen and Kurani, 2009), charging availability in base year of 2010 is assumed that 52% of consumers have Level 1 home charging and the rest do not have home charging; 5% of consumers have Level 1 workplace charging in 2010 and the rest do not have workplace charging; public charging

[2] Ultra-fast charging that can fully charge a EV within minutes is not considered in this study

availability in 2010 is zero, i.e., the probability that an charging opportunity is available at a visited public place is zero. The following scheme is used to simulate future charging availability uncertainty. First, home Level 2, workplace and public charging availability are assumed to linearly increase to 2050 level, whereas home Level 1 linearly decrease to 2050 level. Home Level 1 availability decrease rate is one half of home Level 2 increase rate, i.e., half of home Level 2 are installed in houses with Level 1 chargers and thus replace them and half of Level 2 are installed in houses without Level 1 chargers. Second, home Level 2 availability at 2050 (#17 in Table 4) is assumed to follow a uniform distribution with minimum value of 25% and maximum value of 75%. Same distributions are assumed for workplace and public charging availability (#18-#19 in Table 4). The availability level of home, workplace, and public charging are likely correlated. @Risk allows users to specify a correlation matrix to represent correlations of random variables and the simulation will sample the variables according to the matrix. We have experimented with the following matrix (Table 5). The design is by no means definitive, but just used to illustrate the effect of possible correlations in uncertainty simulation.

3 RESULTS

One thousand simulations were carried out using the probability distributions for the 19 parameters shown in Table 4. All parameters, except home, workplace, and public charging availability, are assumed to be independent. Charging availability parameters are correlated according to the correlation matrix in Table 5. Simulation results are summarized as follows.

3.1 Market Share Uncertainty

Market shares at the baseline scenario are shown in Figure 3, where parameter values are in MA3T default level, i.e., mean values in Table 4. In 2050, PEV share is 50%, with BEV 29% and PHEV 21%. Conventional vehicles (gasoline and diesel vehicles) still account for 34% of new vehicle sales and the remainder is HEV sales. The drop of PHEV and BEV market shares around 2017 is due to expiration of the current PEV federal incentive.

The simulated uncertainty about the market's response to PEVs is illustrated by Figure 4, which shows the mean, 5% and 95% percentile, and ± 1 standard deviation of each year's PEV market share. Note that the mean market share curve doesn't correspond to the baseline scenario in Figure 3.

Further details of the market response are shown by Figure 5, the frequency distributions for the market shares of PHEVs and BEVs in 2030 and 2050. PHEV share distribution in 2030 ranges from 0 to 30% with a mean of 10%. It has a "spike" near zero, indicating the risk of low penetration of PHEVs. PHEV share distribution in 2050 has the similar range with a higher mean of 17%. The "spike" near zero still exists in 2050, though much smaller. On the other hand, distributions for BEV shares in 2030 and 2050 are relatively more symmetric with mean values of 11% and 28% respectively.

The “spike” of PHEV distributions was further investigated. A key factor is the relatively high prices of PHEVs. Table 2 shows that PHEV prices are still significantly higher than conventional ICE vehicles even in 2050. We also found that scenarios with low PHEV penetration (PHEV share in 2030 is less than 10% percentile of its distribution) all have very high price sensitivities (>90% percentile of the parameter’s distribution) and high value of make/model diversity (>82% percentile). Therefore higher upfront purchase price, coupled with consumers’ high sensitivity to price and strong valuation of make/model diversity, may imply very low PHEV penetration. By contrast, BEV prices decrease rapidly after 2030 and are only a few hundred dollars more expensive than ICE vehicles in 2050. This ensures that BEVs achieve moderate penetration even under unfavorable conditions such as high price sensitivity, low gasoline/diesel prices and high value of make/model diversity (see Figure 5 that shows minimum BEV share in 2050 is 12%).

The simulation results demonstrate that the future market for electric drive vehicles is highly uncertain and there is substantial risk in the early and mid-term PEV market. The next section is devoted to a comprehensive analysis of key factors that influence PHEV and BEV market shares.

3.2 Key Determinants

Tornado charts are used to show the relative importance of input parameters in contributing to the variability of PEV penetration. On the left of tornado charts are input parameters ranked according to their importance, with the most important parameter at the top. On the right are bars with the length indicating the strength of the correlation between parameters and PEV shares.

The number along a bar is the parameter's regression coefficient, representing the change of market share in the unit of its stand deviation if the input parameter changes by one standard deviation. For example, the most top coefficient in Figure 6 reads that PHEV share in 2030 decreases by 0.78 standard deviations if price sensitivity increases by one standard deviation and other parameters are held constant in their baseline values.

Figure 6 through 9 are tornado charts for PHEV and BEV shares in 2030 and 2050. Here are some observations:

- Price sensitivity (price slope multiplier bar in tornado charts) is the most important parameter for PHEV shares. The sign of price sensitivity bar is negative for 2030 and 2050 PHEV shares and 2030 BEV share, but positive for 2050 BEV share. Insensitivity to price indicates that consumers put less weight on vehicle prices and pay more attention to other vehicle attributes (e.g., environmental friendliness of the technology) in purchase decision making; whereas high price sensitivity implies that consumers will switch from one alternative to another for even a small change in price. Therefore, lower price sensitivity is favorable to PEV penetration in early period when PEVs are significantly more expensive than competitors like ICEs, On the other hand, BEV prices decrease quickly and become comparable to ICE prices in 2050. Moreover, BEVs have much lower energy cost. Thus higher price sensitivity increases BEV market share in 2050.
- Energy cost perceived by consumers is important to the penetration of both PHEVs and BEVs, as indicated by the position of perceived vehicle life and gasoline/diesel

prices bars on the charts. Perceived vehicle life determines how many years of energy cost savings consumers will value in purchase decisions and thus positively correlates with PHEV share. However, for BEVs, perceived vehicle life is also related to how consumers estimate range assurance cost. The model calculates *range assurance cost* as the product of penalty cost per day and the number of days in the vehicle's lifetime at which daily mileage exceeds BEV's range. Therefore the impact of perceived vehicle life on BEV share is a mixed effect: the longer perceived vehicle life, the larger perceived energy cost savings but the bigger range assurance cost. The net impact is that longer perceived vehicle life moderately increases BEV market share.

- Charging infrastructure availability and range assurance cost are critical to the success of BEV acceptance. For example, home level 2 availability is the most important factor contributing to the variability of BEV share in 2050. The ranking of charging availability according to their impact on BEV adoption is home level 2, public, and workplace. The ranking is consistent with the perception that level 2 is essential to BEVs and home is the most important charging location. Compared with workplace charging, public charging provides more assurance for unplanned long trips.
- Progress of battery cost reduction is important to both PHEV and BEV shares in 2030, but not so much to PHEV and BEV shares in 2050, since battery costs in different scenarios are assumed to converge after 2030 (see Figure 2).
- How consumers value make and model diversity are negatively correlated with PHEV and BEV shares, i.e., the more weight consumers put on make and model diversity, the less likely they are to purchase PEVs. This parameter is more important

to early market of PEVs than late market. Market provision of PEV make and model is also moderately important.

- The percentage of early adopters is among top factors on all 4 charts. As expected, late majority's risk aversion is negatively correlated to the acceptance of PEV and early adopters' WTP for innovative technologies is positively correlated. Note that early adopter's WTP is represented as a negative cost in the MA3T. Thus the tornado charts tell that the larger WTP in absolute value (the smaller WTP), the larger the market share is.
- Tornado charts also show some competition effects between PHEVs and BEVs. For example, range assurance cost, one of the biggest barriers for BEVs, turns out to be positively correlated to PHEV adoption (see Figure 6 and 8).

3.3 Effect of Public Policies

To illustrate the potential role of public policies in PEV market penetration and uncertainty reduction, we re-run Monte Carlo simulation by assuming that the progress of battery cost reduction is accelerated by 5 years and charging infrastructure deployment is at maximum level (75% public and workplace charging availability in 2050). Other model parameters remain as probability distributions in Table 4. Figure 10 demonstrates the effect of accelerated battery progress and infrastructure deployment on market penetration. As expected, PEV share distribution is shifted upward, but surprisingly, the uncertainty of market share is not noticeably reduced, and even increased in the mid-term around 2025. This means that continued battery R&D and charging infrastructure deployment alone won't reduce market share uncertainty, but can substantially increase the expected market share. It also implies that the above battery and infrastructure efforts may reduce PEV market risk (i.e. extremely low market share) while increasing the chance of great success (i.e. very high PEV market share).

4 CONCLUSIONS AND DISCUSSIONS

This study analyzes the uncertainty of PHEV and BEV market penetration using the MA3T model and @risk software. With the help of @risk, the MA3T model is run in a Monte Carlo simulation setting by sampling probability distributions of 19 parameters in energy price, technology progress, market behavior and consumer preferences, as well as charging infrastructure availability. The simulation results suggest that the future market for PEVs is highly uncertain and there is a substantial risk of low PEV penetration in the early and mid-term market. Continued improvement of battery technologies and deployment of charging infrastructure alone do not necessarily reduce market share uncertainty, but can help reduce PEV market risk (i.e. extremely low market share) while increasing the chance of great success (i.e. very high PEV market share).

Top factors that contribute to the variability of PEV market shares are price sensitivities, energy cost, range assurance related cost and charging infrastructure availability. Lower price sensitivity is favorable to PEV penetration in the early period, whereas higher price sensitivity increases BEV market share in the later period when BEV price is reduced to the level of ICE price. Higher gasoline/diesel prices increase the attractiveness of PEVs. Perceived vehicle life decides how many years of energy savings are valued by consumers and it has a strong positive correlation with PHEV share. However, for BEVs, perceived vehicle life is also related to how consumers estimate range assurance cost. The impact of perceived vehicle life on BEV share is a mixed effect: the longer perceived vehicle life, the larger perceived energy cost savings but also the bigger range assurance cost. The net effect is that perceived vehicle life is positively correlated with BEV market share. Charging availability coupled together with perceived vehicle life and inconvenience cost per day when BEV range is insufficient determine range assurance cost and contribute most significantly to the variability of BEV shares in later years when BEV price is comparable to conventional vehicles. Acceleration of battery cost reduction boosts PEV sales in earlier years but has no long term impact.

The study findings are subject to the limitations of the nested logit modeling method (specifically the MA3T model), the selected combination of random parameters, and assumed probability distributions of random parameters. The combination of random parameters is selected according to the literature and also our own judgment. Probability distributions of random parameters have been calibrated to the best information available in the literature. However, at this early stage of PEV market commercialization, much of the market behavior remains unknown. Simplified assumptions have to be used when information is not available. With these caveats, we want to caution the readers that the results from the Monte Carlo simulations, particularly, Figure 4 and 5, are only an illustration of future market uncertainty. We will feel more comfortable if the readers view this study as a sensitivity analysis which varies the parameters of the consumer choice model in the space define by the assumptions in Section 2 and examines the response of the model – market shares. Thus, those tornado charts in Figure 6 to 9 are probably the most important results of this study.

Our intention in this paper is to establish a framework and generate some initial insights toward understanding this important issue of PEV market uncertainty. At the minimum, this paper provides a reference, both in terms of study framework and results, for PEV market uncertainty studies using nested logit models. It is our hope that this study will stimulate more research in learning market behavior. The study itself will be updated when more information is available.

Understanding the uncertainty of PEV market has important implications. First, it provides policy makers with a more realistic description of the challenge they face in attempting to promote PEVs for accomplishing energy security and emission reduction goals. Second, it helps to identify critical factors that influence the acceptance of PEVs. The more that can be learned about these factors, the more likely it is that effective and efficient policies can be designed and implemented.

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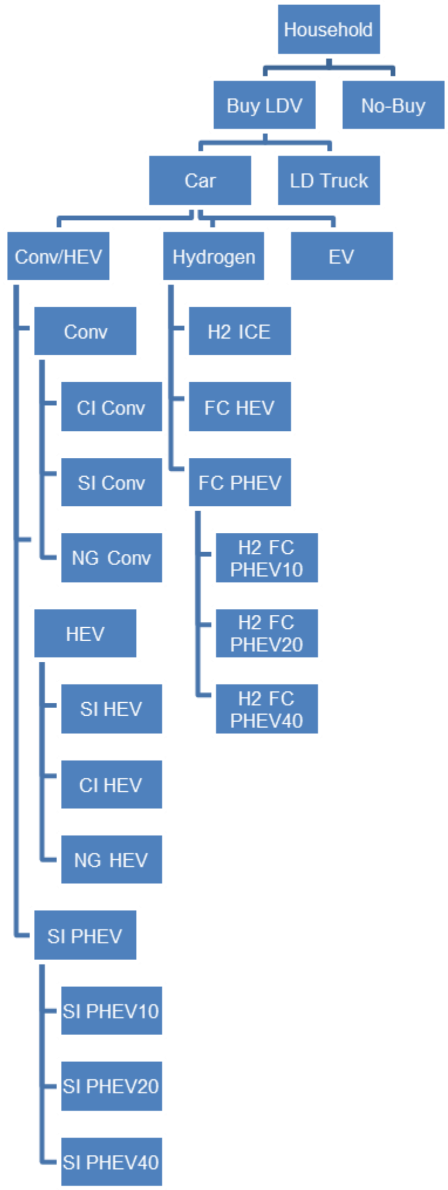

Figure 1Nesting Structure in the MA3T Model.

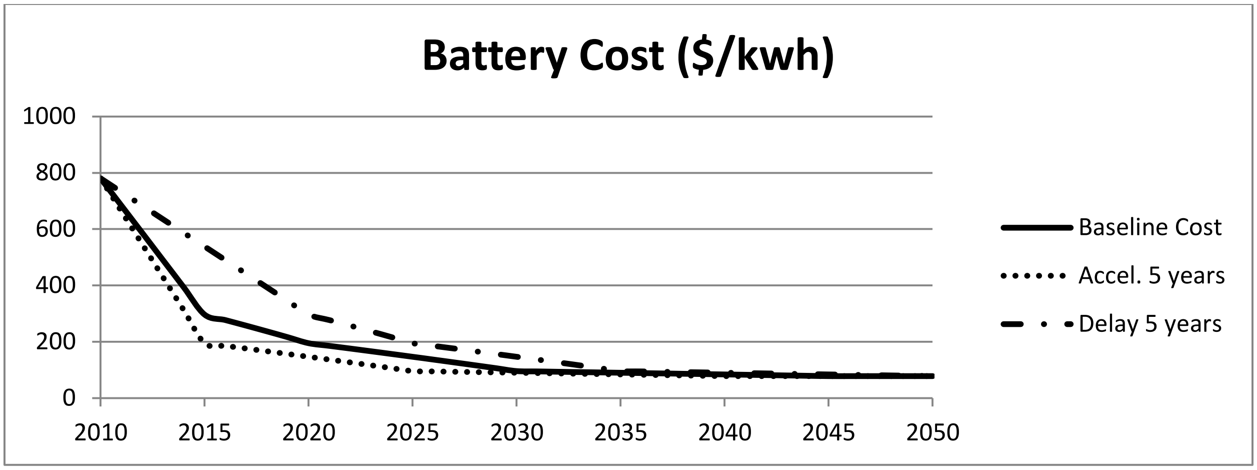

Figure 2 Battery cost scenarios: Baseline, accelerated by 5 years, and delayed by 5 years.

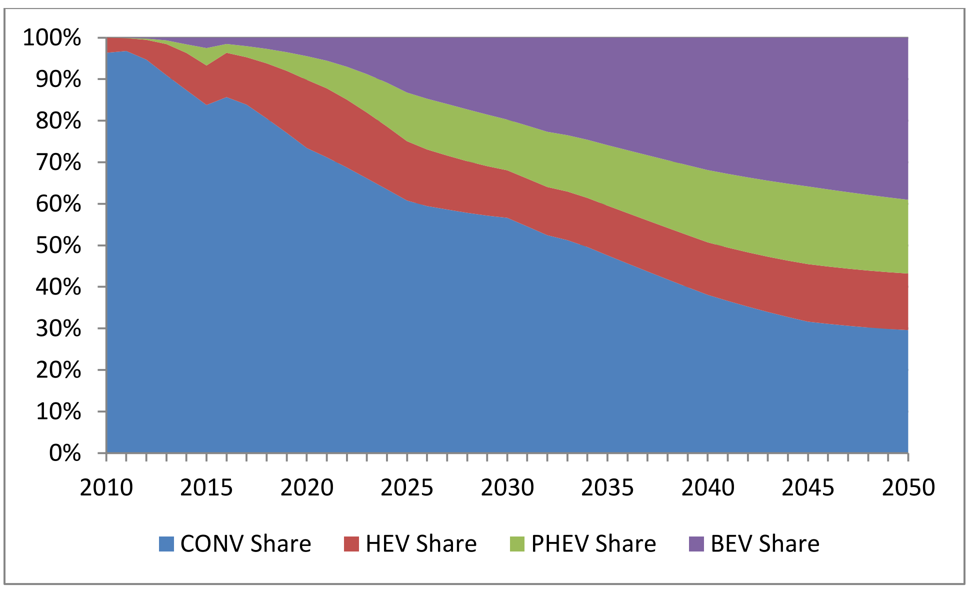

Figure 3 Vehicle technology market shares at the baseline scenario.

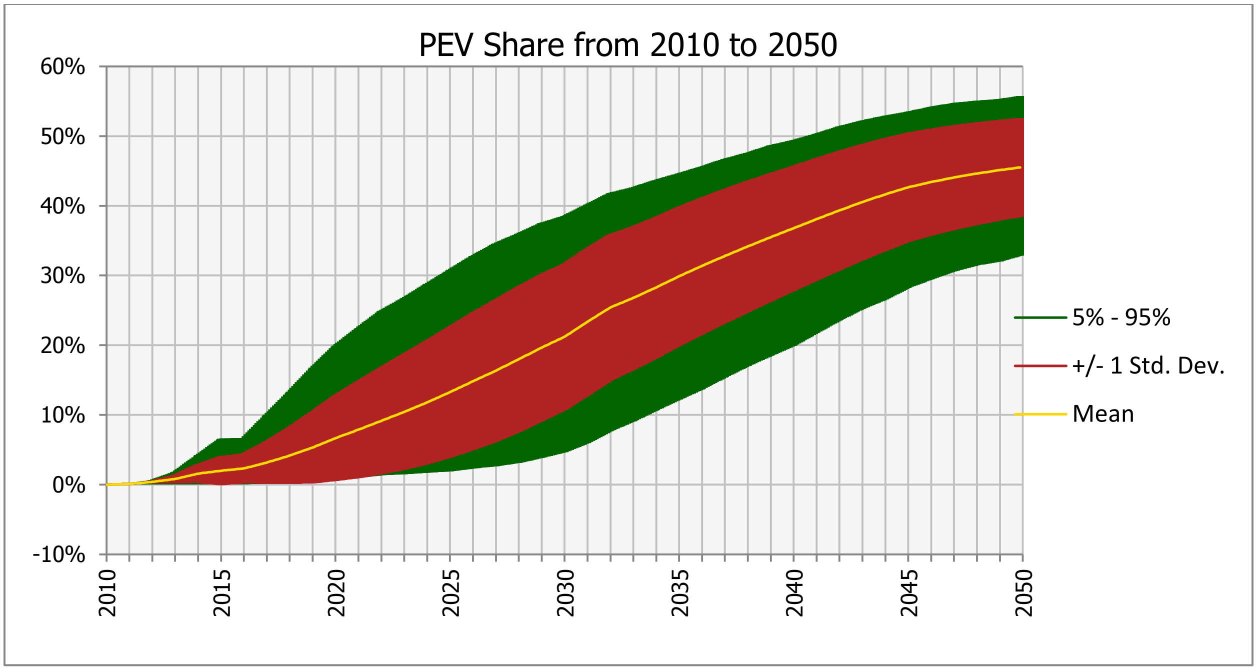

Figure 4 Distribution for PEV share from 2010 to 2050 generated by Monte Carlo simulation.

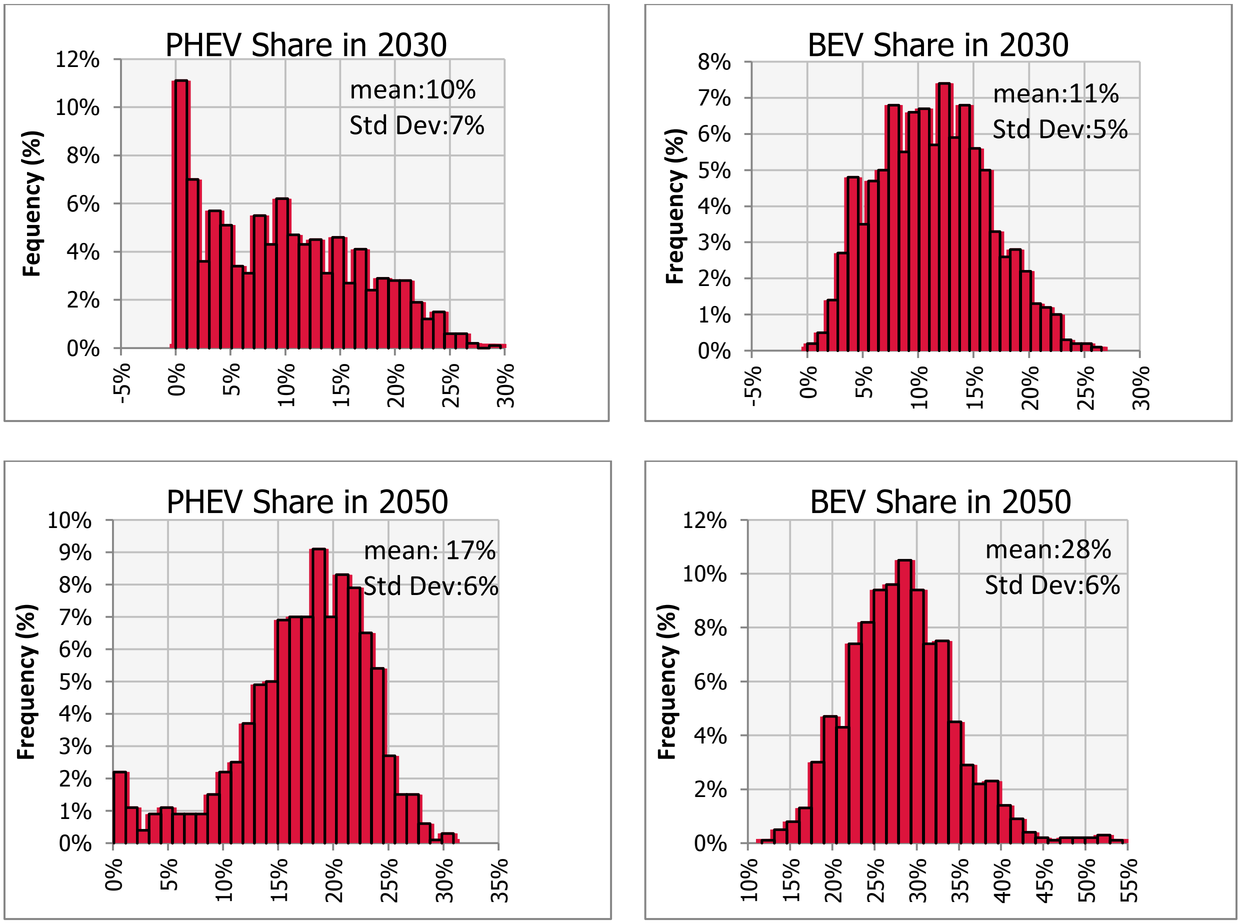

Figure 5 Relative frequency distribution of PEV market shares in 2030 and 2050 generated by Monte Carlo Simulation.

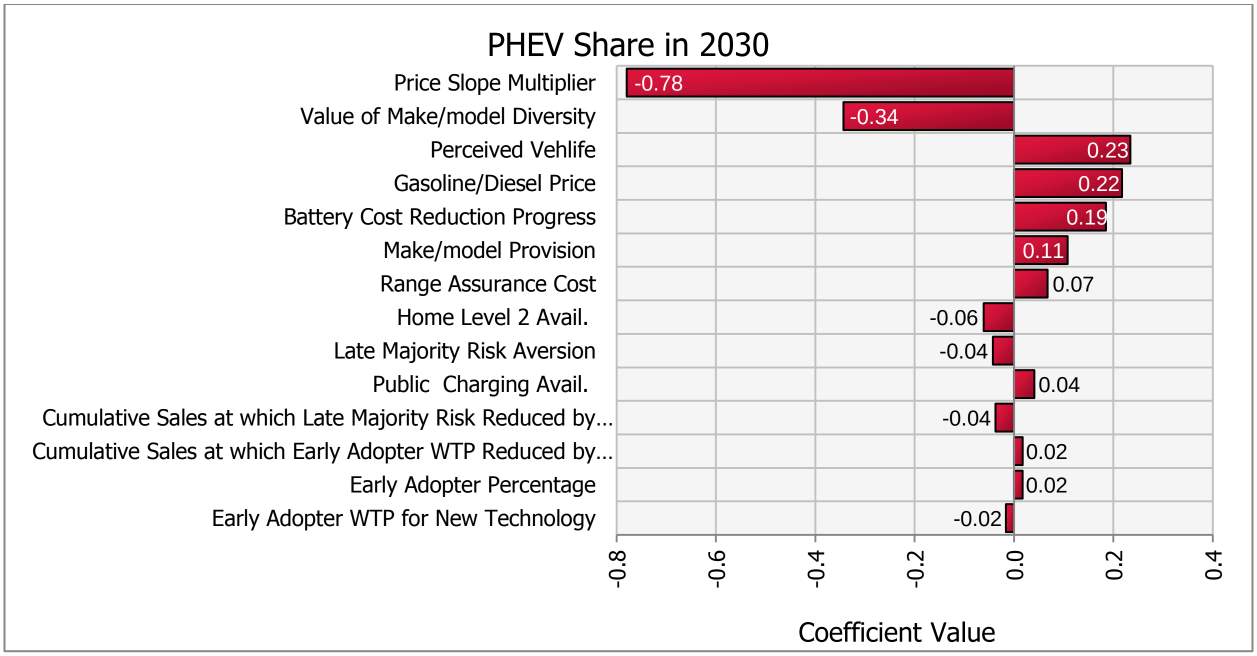

Figure 6 Tornado chart for PHEV share in 2030.

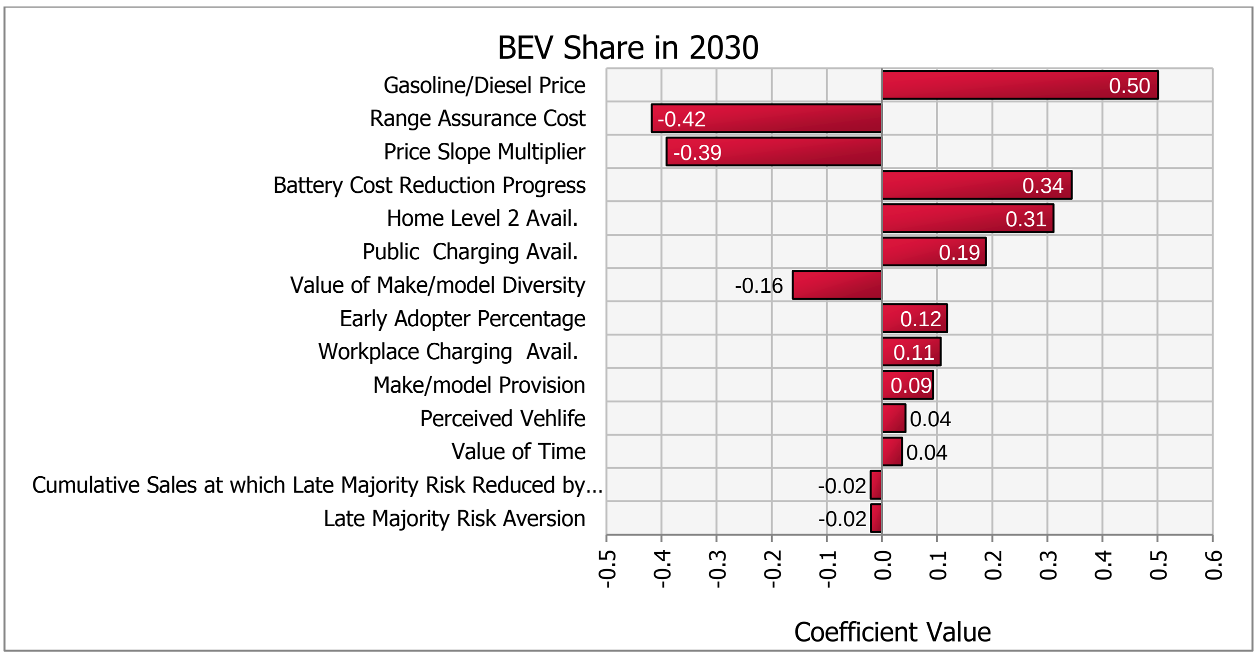

Figure 7 Tornado chart for BEV share in 2030.

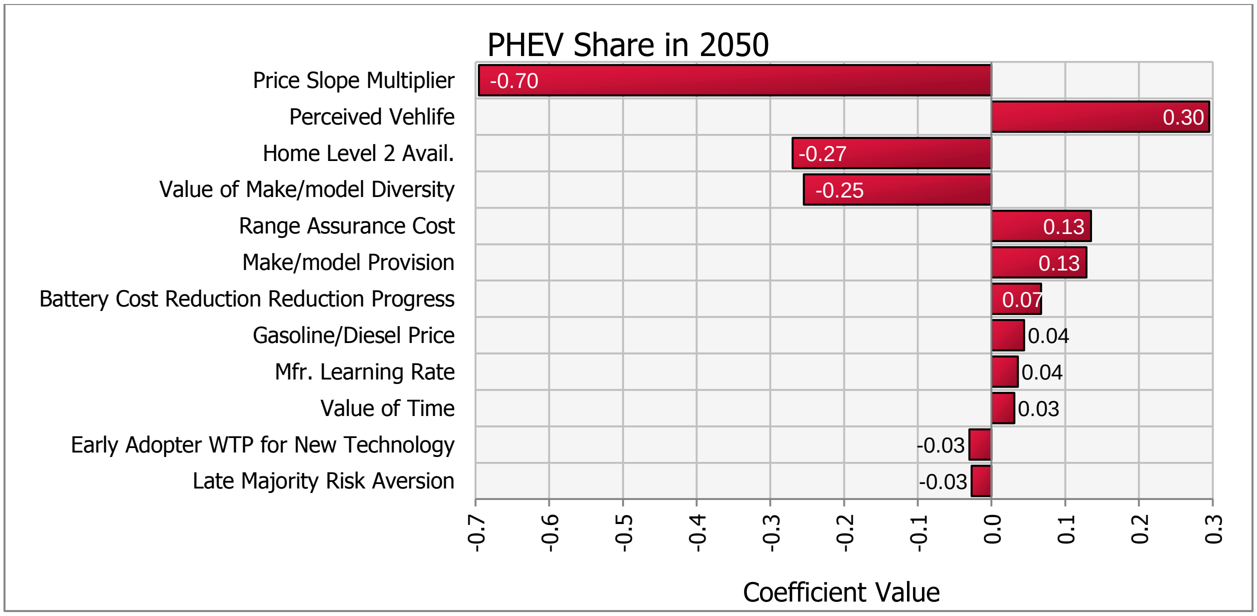

Figure 8 Tornado chart for PHEV share in 2050.

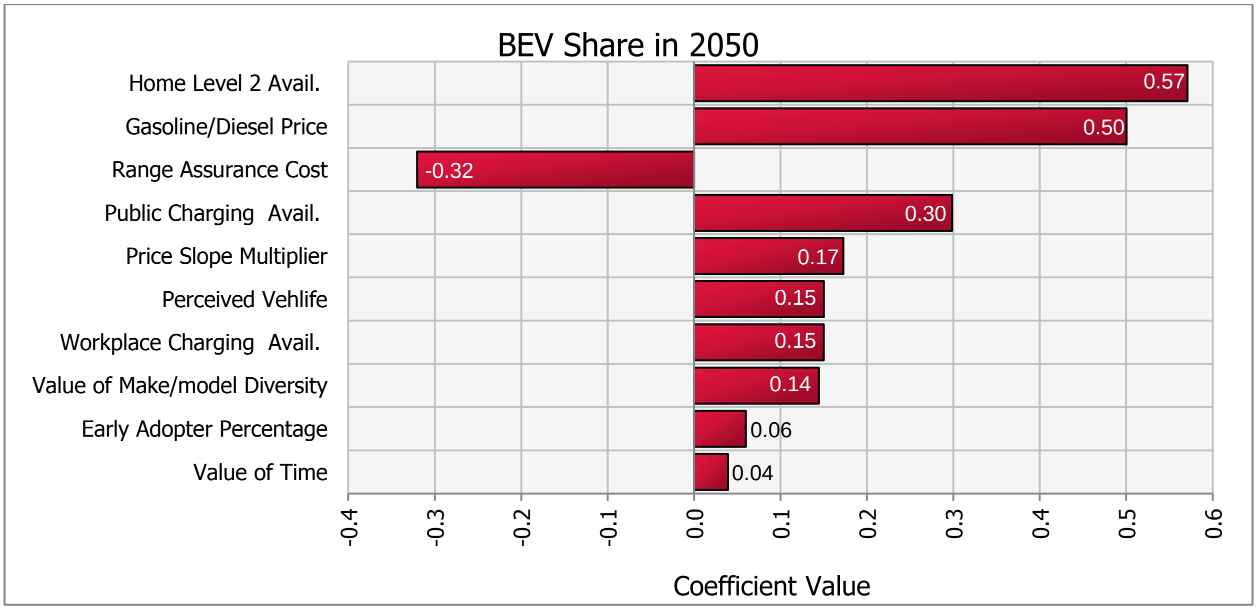

Figure 9 Tornado chart for BEV share in 2050.

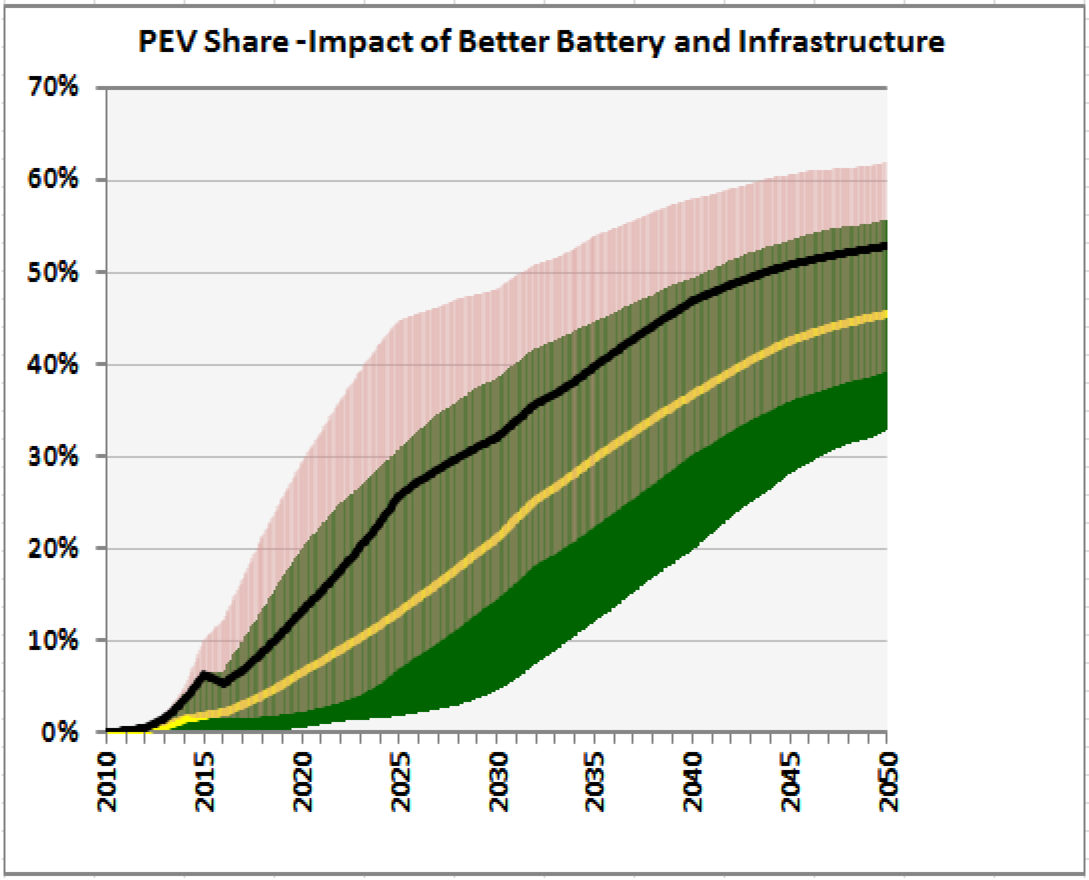

Figure 10 Effect of accelerated battery technology progress and infrastructure deployment on PEV market share: the green area is PEV share distribution given original parameter assumptions in Table 4 and yellow curve is mean market share; while the pink shaded area is share distribution with accelerated battery cost reduction and infrastructure deployment and the black curve is mean market share.

Table 1 MA3T Consumer Segmentation

Region	Area	Home Charging	Work Charging
01_NewEngland	Urban	Level I	Yes
02_MiddleAtlantic	Suburban	Level II	No
03_EastNorthCentral	Rural	None	
04_WestNorthCentral			
05_SouthAtlantic			
06_EastSouthCentral		**Attitude**	**Driver**
07_WestSouthCentral		Early Adopter	Modest Driver
08_Mountain		Early Majority	Average Driver
09_Pacific		Late Majority	Frequent Driver

Table 2 List of Technology Abbreviations

Abbreviation	Description
SI Conv Car	Spark Ignition Conventional Car
CI Conv Car	Compression Ignition Conventional Car
SI HEV Car	Spark Ignition Hybrid Electric Car
CI HEV Car	Compression Ignition Hybrid Electric Car
SI P10 Car	Spark Ignition Plug-in Hybrid Electric Car with 10 miles of Charge-Depleting Range
SI P20 Car	Spark Ignition Plug-in Hybrid Electric Car with 20 miles of Charge-Depleting Range
SI P40 Car	Spark Ignition Plug-in Hybrid Electric Car with 40 miles of Charge-Depleting Range
BEV100 Car	Battery Electric Car with 100-mile Range
BEV200 Car	Battery Electric Car with 150-mile Range
BEV300 Car	Battery Electric Car with 250-mile Range
SI Conv LTK	Spark Ignition Conventional Light-duty Truck
CI Conv LTK	Compression Ignition Conventional Light-duty Truck
SI HEV LTK	Spark Ignition Hybrid Electric Light-duty Truck
CI HEV LTK	Compression Ignition Hybrid Electric Light-duty Truck
SI P10 LTK	Spark Ignition Plug-in Hybrid Electric Light-duty Truck with 10 miles of Charge-Depleting Range
SI P20 LTK	Spark Ignition Plug-in Hybrid Electric Light-duty Truck with 20 miles of Charge-Depleting Range
SI P40 LTK	Spark Ignition Plug-in Hybrid Electric Light-duty Truck with 40 miles of Charge-Depleting Range
BEV100 LTK	Battery Electric Light-duty Truck with 100-mile Range
BEV200 LTK	Battery Electric Light-duty Truck with 150-mile Range
BEV300 LTK	Battery Electric Light-duty Truck with 250-mile Range

Table 3 Vehicle Prices in MA3T (2005$)

Technology	2015	2020	2030	2050
SI Conv Car	$19,795	$21,090	$20,236	$21,347

CI Conv Car	$22,284	$24,136	$22,948	$22,715
SI HEV Car	$24,178	$25,970	$25,672	$24,495
CI HEV Car	$30,184	$29,062	$26,864	$26,027
SI P10 Car	$30,611	$28,032	$26,674	$25,153
SI P20 Car	$34,788	$30,323	$27,827	$25,984
SI P40 Car	$36,134	$32,986	$29,215	$27,247
BEV100 Car	$31,136	$27,941	$22,982	$22,000
BEV200 Car	$48,603	$37,113	$26,935	$25,174
BEV300 Car	$64,107	$46,285	$30,888	$28,347
SI Conv Light Truck	$21,199	$22,546	$22,101	$23,228
CI Conv Light Truck	$31,195	$25,219	$25,799	$24,349
SI HEV Light Truck	$29,953	$28,343	$28,222	$26,927
CI HEV Light Truck	$32,786	$31,115	$29,186	$28,257
SI P10 Light Truck	$34,591	$30,932	$29,758	$27,958
SI P20 Light Truck	$40,124	$33,945	$31,399	$29,155
SI P40 Light Truck	$46,371	$36,622	$32,811	$30,480
BEV100 Light Truck	$41,570	$31,312	$26,259	$24,995
BEV200 Light Truck	$58,167	$42,855	$31,663	$29,273
BEV300 Light Truck	$78,304	$54,397	$37,068	$33,551

Table 4 Probability Distributions for Model Parameters Used in Monte Carlo Simulation

No.	Parameters	Distribution	Min	Mean	Max
1	Gasoline and diesel price multiplier	Triangle	0.5	1	1.5
2	Years of acceleration for Battery Cost Reduction	Triangle	-5	0	5
3	Learning rate multiplier	Uniform	0.5	1	1.5
4	Price elasticities of vehicle choice relative to standard assumptions	Triangle	0.5	1	1.5
5	Make/Model provision multiplier	triangle	0.5	1	1.5
6	Make/Model diversity value multiplier	Uniform	0.5	1	1.5
7	Value of time ($/hr.)	Triangle	$10	$20	$30
8	BEV range assurance cost multiplier	Triangle	0.5	1	1.5
9	Perceived vehicle life (yrs.)	Triangle	2.5	5	7.5
10	Percentage of new car buyers who are early adopters	Uniform	5.0%	10.0%	15.0%
11	Willingness of early adopters to pay for novel technology ($)	Uniform	$1217	$2433	$3649
12	Cumulative sales at which early adopters WTP is reduced by 1/2	Uniform	1,000,000	2,000,000	3,000,000
13	Early Majority's aversion to risk of new technology ($)	Uniform	$363	$725	$1088
14	Cumulative sales at which early majority's risk is reduced by 1/2	Uniform	1,000,000	2,000,000	3,000,000
15	Late Majority's aversion to risk of new technology ($)	Uniform	$1915	$3827	$5738
16	Cumulative sales at which late majority's risk is reduced by 1/2	Uniform	1,000,000	2,000,000	3,000,000
17	Home Level 2 avail. In 2050	Uniform	25%	50%	75%
18	Workplace charging avail. in 2050	Uniform	25%	50%	75%
19	Public charging avail. in 2050	Uniform	25%	50%	75%

Table 5 Correlation Matrix for Charging Availability Parameters

Correlations	Home Level 1 Avail.	Home Level 2 Avail.	Workplace Avail.	Public Avail.
Home Level 1 Avail.	1			
Home Level 2 Avail.	0.5	1		
Workplace Avail.	0.2	0.2	1	
Public Avail.	0.2	0.2	0.7	1

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