DOCKETED	
Docket Number:	20-IEPR-02
Project Title:	Transportation
TN #:	235770
Document Title:	Relative Economic Competitiveness of Light-Duty Battery Electric and Fuel Cell Electric Vehicles
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Filer:	Raquel Kravitz
Organization:	California Energy Commission
Submitter Role:	Commission Staff
Submission Date:	11/20/2020 3:20:08 PM
Docketed Date:	11/23/2020

Relative Economic Competitiveness of Light-Duty Battery Electric and Fuel Cell Electric Vehicles

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Abstract

This paper estimates battery electric (BEV) and hydrogen fuel cell electric vehicle (FCEV) costs from today through 2040 to explore the potential market size of each vehicle type. Two main tasks are performed. First, the total cost of ownership (TCO) – including vehicle purchase, fuel, maintenance, resale, and refueling inconvenience – is estimated for 77 light-duty vehicle (LDV) segments, defined by driving range and size class. Second, data on individual travel behavior is used to estimate the fraction of vehicle owners within each of the 77 segments. In 2020, BEVs are estimated to be the cheaper vehicle option in 79 to 97 percent of the LDV fleet and have a weighted average cost advantage of $0.41 per mile below FCEVs across all vehicle segments and drivers. However, costs of the two powertrains quickly converge between 2025 and 2030. By 2040, FCEVs are estimated to be less expensive than BEVs per mile in approximately 71 to 88 percent of the LDV fleet and have notable cost advantages within larger vehicle size classes and for drivers with longer daily driving ranges. This analysis demonstrates a competitive market space for both FCEVs and BEVs to meet the different needs of LDV consumers.

Keywords: electric vehicles, market segmentation, fuel cell vehicles, total cost of ownership, hydrogen, greenhouse gas abatement.

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Figure 1: Frequency distribution of two example individuals of daily miles driven over an entire year. Person A (green) has a higher number of short-mileage days than Person B (black). A 150-mile range BEV would satisfy Person A on all but 1 of 365 days per year, whereas a 200-mile range BEV would satisfy Person B all but 5 of 365 days per year.

Figure 2: Cumulative frequency distribution of maximum daily mileage, by number of days of inconvenience. Dashed black line is the cumulative frequency distribution of daily average distance (i.e., total mileage reported in 2009 NHTS for respondent's travel day).

Figure 3: Difference in TCO of FCEV and BEV ($Cost_{FCEV}$ - $Cost_{BEV}$) for 2020 and 2040. Red indicates favorable TCO for BEVs. Green indicates favorable TCO for FCEVs.

Figure 4. Fraction of LDV fleet that is cost competitive for FCEVs (BEVs) as a function of days of inconvenience per year. Inconvenience penalty is assessed to vehicles that do not belong to a multi-vehicle household.

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1. Introduction

Battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs) are two promising all-electric powertrains that could help reduce emissions and petroleum use from on-road vehicles (National Research Council, 2013; Williams et al, 2015; Argonne National Laboratory 2016a; Sims et al., 2014). A common notion among automakers is that BEVs will compete among smaller vehicle size classes with shorter driving ranges, and that FCEVs will compete among larger vehicle size classes with longer daily ranges (e.g., Eberle and von Helmolt, 2010).

A key factor that drives this assumed market segmentation is the difference in mass compounding. For BEVs, as the capacity of the battery pack increases, an ever-greater fraction of that capacity is used to move the mass of the batteries rather than the mass of vehicle, passengers, and cargo. This results in a nonlinear relationship between vehicle purchase cost and vehicle range. For FCEVs, after adding the basic components of the powertrain – i.e., the compressed gaseous storage tank, fuel cell, balance of plant components, and small battery – an increase in vehicle range requires only slightly larger components, which has a relatively small impact on vehicle mass and cost. Differences in mass compounding between BEVs and FCEVs may also be visible across vehicle size classes as the ratios of mass, stored energy, and range change.

This paper advances the conceptual framework of mass compounding described above by examining costs of light-duty BEVs and FCEVs across a spectrum of vehicle driving ranges and size classes. Total cost of ownership (TCO) – including the time discounted vehicle purchase, operating, and maintenance cost – is estimated for FCEVs and BEVs for 77 market segments, defined by vehicle size class and vehicle effective range between refueling. Additionally, costs of range-related inconveniences are added to each vehicle segment. This segmentation helps elucidate the relative economic competitiveness of BEVs versus FCEVs into the future.

The paper is rooted in literature that examines costs, benefits, and consumer valuation of alternative fuel vehicles and refueling availability. The National Research Council (2013) uses a TCO vehicle model to conduct a sweeping comparison of four pathways to reduce light-duty vehicle (LDV) greenhouse gas (GHG) emissions out to 2050: (1) efficient internal combustion engine vehicles (ICEVs), (2) biofuels used in ICEVs, (3) BEVs, and (4) FCEVs. They find that none of the four pathways, by itself, is projected to achieve sufficient reductions in GHG emissions to meet deep decarbonization goals in 2050.

Other literature offers more focused examinations of a single factor that will determine the size of the future BEV market, such as vehicle use patterns (Pearre et al., 2011; Lin et al., 2012; Barter et al., 2015; Tamor et al., 2015; Tamor and Milacic, 2015) and household-level characteristics (Khan and Kockelman, 2012; Axsen and Kurani, 2012; Tal et al., 2013; Björnsson and Karlsson, 2017; Karlsson, 2017). Other studies examine the influence of incentives, vehicle characteristics, infrastructure availability, or other factors on early market BEV adoption (Sierzchula et al., 2014; Sheperd et al., 2012; Krause et al., 2016). Optimum BEV range is estimated by Lin et al. (2014), while optimum introduction of BEVs into the market is estimated by Kontou et al. (2017). Earlier, Delucchi and Lipman (2001) identified the vehicle component cost and performance characteristics that must be met for BEVs to be competitive with incumbent technologies. Palmer et al. (2018) examine the historical link between TCO and market share for BEVs, hybrid, and plug-in hybrid electric vehicles.

Relatively few studies examine the potential market size of FCEVs or attempt to segment the market into individual size classes. A simple method to segment vehicle markets is a "constraints analysis" in which one or more variables (e.g., access to at-home charging) constrains the maximum or minimum possible market size (Williams and Kurani, 2006). Another approach is to use a consumer choice model that captures vehicle purchase decisions at the individual level, then aggregates to an economy-wide level (e.g., Lin et al.'s (2013) *Market Acceptance of Advanced Automotive Technologies Model* (MA^3T)). Kast et al. (2017) use daily operational range to estimate the feasibility of converting 10 categories of medium and heavy truck classes to fuel electric trucks.

This paper provides a unique technology-behavioral cost perspective to estimate the competitive market size of LDV BEV and FCEV vehicle classes. BEVs and FCEVs are compared because they are two promising powertrains that can enable energy security via the reduction of U.S. oil imports in addition to deep greenhouse gas (ANL, 2016a) and air pollutant emissions reductions (Williams et al., 2015). Although this simplistic two-vehicle world ignores the many competing vehicle technologies (like hybrid electric vehicles), a clearer understanding about the potential size and relative costs of the two vehicle markets can help policy makers prioritize investment decisions.

Section 2 of the paper presents the methods for estimating the TCO and daily mileage requirements of U.S. drivers. Section 3 presents results comparing the TCO for 77 size class-range segments. Section 4 presents a sensitivity analysis for key assumptions. Section 5 discusses the results, and details how assumptions made by the authors to simplify the analysis might be affect the analysis conclusions. Finally, Section 6 offers the author's conclusions. The paper's goal is to examine the potential market sizes for BEVs and FCEVs, and to identify the size class/range segments most favorable to each powertrain, from today to the year 2040.

2. Methods

2.1 Total Cost of Ownership of BEVs and FCEVs

2.1.1 Estimating TCO from Autonomie

The non-linear relationship between vehicle mass, range, cost, and size class results in a complex vehicle design space. To depict this space, this paper uses the U.S. DOE's *Autonomie* model to project vehicle component-level costs of FCEVs and BEV-50s through BEV-300s (at 50-mile increments) for the years 2020-2040. *Autonomie* is a forward-looking, vehicle simulation model that enables the comparison of vehicle powertrain configurations and component technologies on a consistent basis. *Autonomie* performs ground-up estimates of the size and type of components necessary to build a vehicle, from which it estimates a vehicle's fuel efficiency and cost. Further details can be found in ANL (2016b). Assumed component costs and fuel prices specific to this analysis are described below and given in greater detail in the Appendix. This paper's calculations assume a five-year lag between costs from *Autonomie* and real-world costs (i.e., *Autonomie* output for the year 2015 are assumed to be real-world costs in 2020), given the typical five-year lag time from initial vehicle R&D to retail sales. This five-year lag has been applied to *Autonomie* data in other analyses (see, e.g., ANL, 2016a).

Five post-hoc calculations are performed on the output of *Autonomie*, as described below and in Sections 2.1.2 to 2.1.5. The first post-hoc calculation is to calculate the net present value of TCO per mile for each vehicle range-size segment. This calculation methodology follows those used elsewhere (e.g. Lin, 2014; Kontou et al., 2017). A vehicle purchase payment is assumed to be made only once at the beginning of a vehicle's life, but fuel purchases are made regularly over the life of the vehicle. At the end of five years, the vehicles are sold on the used vehicle market for their depreciated price and the revenue is returned to the vehicle owner. The TCO in $ per mile is calculated as follows:

$$TCO = \left(\frac{1.5*V+F-R}{Mileage}\right) \quad (1)$$

where *V* is vehicle cost, in constant 2015 U.S. dollars, found by summing the upfront cost of the respective vehicle components. Additionally, *V* is multiplied by a markup value of 1.5 to account for the difference between production cost and sales price at the dealer. *F* is the fuel cost over a five-year period, discounted at real rate of seven percent per year. Vehicle and fuel costs are discussed in greater detail below. *R* is the resale value after five years, which is equal to *V* times 38.2 percent, which is a typical value for vehicles (Edmunds, 2010). *Mileage* refers to the total mileage over the five-year ownership of the vehicle. All vehicles are assumed to be driven 14,231 miles per year in their first year of ownership, declining to 13,028 by year five (Davis et al., 2016). There is some evidence that early adopters of short range BEVs travel fewer miles per year than assumed here. In a year-long study of California households with a plug-in vehicle, Nissan Leafs were driven an average of 10,230 miles per year. Generally, the Leaf was used for shorter-distance trips, whereas internal combustion engine (ICE) vehicles in the household were used for trips longer than 70 miles (Nicholas, 2016). However, no such data on annual vehicle miles traveled exists yet for drivers of FCEVs. Therefore, to maintain a fair comparison of costs, all vehicles are assumed to be driven the same number of miles.

The value of V in a given year for a given size class is the summation of the costs of individual components (ANL, 2016b). For BEVs, vehicle components in V include the battery, motor, glider (the vehicle minus its powertrain, fuel tank/batteries and wheels), wheels, and wiring. Battery costs are assumed to decline from $360 to $165 per kWh for the assembled pack between 2015 and 2040, which is similar to costs in Nykvist and Nisson (2015). For FCEVs, the components in V include a small battery, motor, fuel cell stack, hydrogen tank, balance of plant, glider, and wheels. Because the fuel costs of hydrogen and electricity are not explicitly modeled in *Autonomie,* hydrogen cost (as dispensed at the station) is assumed to be $13 per kg of hydrogen in 2020[1] and decline to $2.50 per kg by 2040. These values assume that the US DOE cost targets are met and also include road taxes, which are assumed to be $0.50 per kg. These are slightly updated values relative to those in (Stephens et al., 2016a), and are used in standard US DOE-funded analyses. Electricity costs are assumed to vary from $0.10 per kWh in 2020 to $0.12 per kWh in 2040, per US DOE's 2016 Annual Energy Outlook Reference Case for transportation customers (US DOE, 2016). The sensitivity analysis in Section 4 demonstrates how higher ultimate hydrogen costs (e.g., $7.00 per kg) impact results.

2.1.2 Scaling Between Vehicle Size Classes

The second post-hoc calculation conducted on the output of *Autonomie* concerns vehicle size class. *Autonomie* estimates costs for five generic vehicle size classes: compact, midsize sedan, small sports utility vehicle (SUV), and pickup truck. Using these estimates, this paper's analysis linearly scales the costs for seven other size classes[2] based on the average curb weight of a representative vehicle in that size class. The curb weights and representative vehicle types are shown in the appendix as Table A-1. The justification for a mass-based interpolation method is that the size of vehicles is expected to be positively correlated with the quantity of embedded materials, manufacturing labor, and scrappage cost, and negatively correlated with the fuel economy. Thus, a heavier vehicle will have larger vehicle purchase cost, larger fuel costs, and higher resale value. It is recognized that this scaling methodology is an approximate method.

2.1.3 Scaling FCEVs to Low Volume Sales

The *Autonomie* model currently estimates costs based on "high-volume" sales of vehicles (i.e., 500,000 vehicles per year). BEV sales have reached this level already if measured at a global level (IEA, 2017). Because annual U.S. FCEV sales are less than 2,000 vehicles per year at the

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[1] This the price of hydrogen at the West Sacramento, California hydrogen station in a recent visit by the authors. Other stations in California have similar hydrogen price.
[2] The additional size classes include: two-seaters, mini-compacts, sub-compacts, large cars, small station wagons, passenger vans, large SUV, and small pickup truck.

time of writing (Cobb, 2017), a third post-hoc calculation is needed to translate high-volume costs to low volume costs – namely for the fuel cell system, gaseous storage tank, and production of hydrogen fuel. For this, a relationship between production volume and cost is needed. Two factors are assumed to reduce costs: (1) learning by doing and (2) scale economies[3]. This paper uses estimates from Greene and Duleep (2013), who find that meeting long-term US DOE cost goals[4] entails progress ratios of 0.94 to 0.96 (i.e., doubling cumulative production decreases costs by 4 to 6 percent) and a scale elasticity of -0.2 (i.e., a 1.0 percent increase in cumulative production decreases costs by 0.2 percent). Figures A-1, A-2, and A-3 in the Appendix show both the high and low volume costs over time for fuel cells, gaseous storage tanks, and hydrogen production and delivery. These figures also show the change in costs with changes in the annual sales of FCEVs, between 1,000 to 500,000 per year. Figure A-4 in the Appendix shows the BEV projected battery costs versus time for different ranges of BEVs. Other FCEV component costs, such as the power electronics, motor, and transmission, are not scaled to low volume because they are assumed to be mature technologies and are consistent with component costs used in BEVs.

To apply progress ratios, a baseline vehicle sales projection is needed. This paper's analysis uses estimates from the California Air Resources Board (CARB, 2015) to project FCEV growth between 2015 and 2020 then continue an upward growth through 2040. Annual sales of FCEVs in the U.S. are assumed to grow from 179 vehicles in 2015 to 3.7 million in 2040, reaching approximately 25 percent of the LDV new vehicle sales in 2040. These sales projections for FCEVs are within the bounds of national deep decarbonization scenarios that achieve an 80 percent reduction in economy-wide emissions by 2050 (Williams et al., 2015). Table 1 shows the assumed FCEV sales growth to 2040 in terms of both sales and percentage of stock. The ramp up rates are comparable to the historical growth of other new powertrains in recent years, including hybrid electric vehicles and BEVs (ANL, 2017).

INSERT TABLE 1 HERE

2.1.4 Estimating Actual BEV Range

The fourth post-hoc calculation performed in this work is to interpolate costs of BEV-50 through BEV-300s at 50-mile range increments, assuming an exponential rate of cost increase, consistent with the mass compounding effect described above. BEV costs are adjusted to reflect that rated BEV range is shorter than actual, on-road range. The net effect is each BEV range is lowered by approximately 10 percent. This BEV range derating is consistent with other analyses (ANL, 2016a).

[3] *Autonomie* already accounts for technological learning –i.e. innovation associated with research and development efforts.
[4] For hydrogen storage, a scale elasticity of -0.1 is used based on input from component suppliers (Greene and Duleep, 2013).

2.1.5 Adding Inconvenience Costs

A fifth and final post-hoc calculation is the addition of an inconvenience penalty associated with vehicle range. For BEVs, drivers are assumed to be inconvenienced any day the driver's maximum daily mileage exceeds the BEV range (e.g., the number of days per year a driver of a BEV-150 wishes to travel more than 150 miles). Similarly, FCEV drivers will be inconvenienced when their daily mileage exceeds the assumed refueling distance of 300 miles. Note, the 300 miles is based on the stated range of 312 miles of a Toyota Mirai FCEV. The FCEV inconvenience cost is applied to years 2020, 2025, and 2030, when inter-city refueling stations are assumed to be limited. Section 2.3 below explains how the range-related inconvenience is estimated.

FCEV drivers are also inconvenienced due to "detour trips." Unlike today's gasoline refueling infrastructure, early hydrogen refueling stations will spaced farther apart, requiring longer refueling trips on average. Kang and Recker (2014) estimate that detour trips result in inconvenience costs of $22 to $39 on refueling days. These costs are the incremental cost to refuel FCEVs above that of ICE vehicles. Kang and Recker's (2014) analysis simulates travel behavior in a network of 36 refueling stations in the greater Los Angeles, California region using the California Household Travel Survey. Travelers have an assumed value of time of $30 per hour. The low estimate of $22 assumes that on refueling days, travelers re-sequence their trips to minimize the inconvenience costs. The high estimate of $39 assumes that on refueling days, travelers maintain the same sequence of trips but minimize the distance of the detour trip. This paper uses the median value for inconvenience cost of $30.5 on refueling days in the year 2020, which equates to $0.10 per mile assuming a refueling every 300 miles. For simplicity, this inconvenience is assumed to decrease to $0.05 per mile by 2025, $0.025 per mile in 2030, and to $0 thereafter as greater numbers of hydrogen stations are built.

The inconvenience cost penalties are added to the TCO costs above in Equation (*1*):

$$TCO_{Total} = \left(\frac{1.5*V+F-R+P}{mileage}\right) \qquad (2)$$

where P is the time-discounted cost of rental cars and detour trips over the 5-year ownership period.

2.1.6 Omitted Costs from TCO Analysis

At least four real or perceived costs are not included in the TCO analysis.

- **Time cost of refueling:** BEVs take longer to refuel that a typical FCEV, for most charging configurations. This could be assessed as a time cost in the TCO analysis. However, early studies of BEV charging behavior indicate that the vast majority of charging takes place at home or at work while the driver does other activities (INL, 2015), thus minimizing the inconvenience associated with the recharge. For this reason, time cost of refueling is not explicitly included in the TCO analysis.
- **Vehicle performance**: Past studies demonstrate that consumers value vehicle performance, such as greater acceleration (e.g., Hidrue et al., 2011). While certain BEVs – e.g., Tesla Model S – undoubtedly have higher acceleration than today's FCEVs, other popular BEV models – e.g., Nissan Leaf – have acceleration times comparable to today's FCEVs. Additionally, it is difficult to predict future FCEV acceleration based on the limited number of models available today. Thus, a formalized acceleration-related cost penalty for FCEVs is not included in this analysis.
- **Capital cost of fuel infrastructure:** the TCO analysis described above assumes the capital cost of refueling infrastructure (e.g., charging stations, electricity lines, hydrogen dispensers, hydrogen pipelines, etc.) is implicitly included in the cost of electricity or hydrogen fuel, just as the cost of gasoline includes the cost of pipelines and refueling stations. This assumption means that government or third-party subsidies for charging equipment or hydrogen refueling stations are not included. The justification for this assumption is that subsidies are not seen directly by vehicle owners and therefore do not factor into vehicle purchase decisions. Another related cost that is not included in the TCO analysis for BEVs is that of at-home charging equipment. This modeling choice is made because (1) at-home charging equipment is optional and (2) it is not clear the fraction of FCEV owners who will purchase at-home hydrogen reformers. To simplify the analysis, all supplemental vehicle refueling costs (outside that of the fuel) are omitted. Finally, the assumed method of recharging BEVs is via plug, but other recharge options like wireless charging have been shown to be viable options (Fuller, 2016).
- **Social costs:** Delucchi and Lipman (2001) describe four social costs associated with the use of BEVs relative to ICE vehicles, including: noise, externalities of oil use, climate change, and air pollution. Delucchi and Lipman estimate these social costs account for \$1.09 per mile savings for BEVs over ICE vehicles. Undoubtedly, differences in social costs exist between BEVs and FCEVs, dependent on the source and transmission of electricity and hydrogen. However, these social costs may not factor into the mental TCO of every vehicle owner. Therefore, they are excluded in this analysis.

2.2 Range Requirements Derivation from Gamma Distribution

Prior research uses two primary data sources to understand range preferences of light-duty vehicle drivers: (1) household travel surveys and (2) vehicles instrumented with Global Positioning System (GPS) units (e.g., Pearre et al., 2011; Khan and Kockelman, 2012; Barter et al., 2015). Across studies on BEVs, a common insight is that the vast majority (90 to 95 percent) of daily miles traveled could be electrified with a 100-mile range BEV. However, after accounting for the inconvenience created on a few days a year when range cannot be met with a single charge, the estimated BEV market size is much smaller. For example, Pearre et al. (2011) use Atlanta, Georgia GPS data in 455 vehicles to calculate that a BEV with a 200-mile range would meet 21 percent of the sample's range needs all the time, 35 percent of the sample if drivers are willing to be inconvenienced two days per year, and 60 percent if drivers are willing to be inconvenienced six days per year. Thus, understanding the distribution of daily miles of drivers over a long period of time (e.g., one year) is crucial to categorizing drivers into vehicle segments.

The main limitation of household travel surveys in these analyses is that most involve just a single day's worth of travel. Since vehicle owners choose vehicles based on a distribution of daily miles travelled and their perception of driving needs, an analysis based on a one-day travel survey will likely underestimate a consumer's true range preference for a vehicle. On the other hand, most GPS datasets are multi-day (or even multi-year) but often limited to a small subset of drivers that may not be representative of the general public. One large GPS dataset is the EV-project coordinated by Idaho National Lab (INL), which tracked the daily mileage of thousands of drivers of Nissan Leafs and Chevy Volts (INL, 2015). However, individual-level travel data is not publicly available.

To overcome the above data limitations, several authors create an artificial daily travel distribution from a one-day travel survey. Greene (1985) suggests using a gamma distribution to translate a single day's worth of data to a longer time frame, such as a year or more. This method is later employed by Lin et al. (2012; 2014), Barter et al. (2015), and Tamor et al. (2013, 2015). Lin et al. (2012) compared the fit of three flexible, non-negative distributions – Gamma, Lognormal, and Weibull – and found the Gamma distribution had the best fit to drivers' real-world one-day travel distance. Tamor et al. (2013; 2015) argue that a five-parameter distribution that includes two sub-functions – one which captures habitual daily travel and one which captures infrequent travel – provides a better fit than a gamma distribution in mapping a single-day travel survey to a daily mileage distribution.

Here, this paper follows Lin et al.'s (2014) methodology to transform travel survey data in the 2009 Department of Transportation National Household Travel Survey (NHTS) to an artificial distribution of daily miles travelled. The 2009 NHTS is a nationally-representative survey that includes roughly 100,000 vehicle-level observations and contains information about the associated driver's household, travel environment, distance to work, and annual mileage (US DOT, 2009). Survey weights provided with the NHTS data are used in this analysis to ensure adequate representation of under-sampled respondents. The 100,000 observations are filtered to 24,134 observations similar to Lin et al. (2014) using the following criteria:

- Respondent recorded a non-zero distance to work
- Age of vehicle is less than or equal to five years
- Vehicle is an LDV and is not a commercial vehicle
- Driver is employed full-time
- Main mode of travel to work is driving

The transformation from a single day of driving to a daily mileage distribution uses two variables in the NHTS: commute distance and annual mileage. Commute distance is transformed to a traveler's most frequent daily mileage (or mode, (M_d)) by multiplying commute distance by 53/22, where 53/22 is the average American's fraction of daily miles to commute miles as determined by the NHTS. A traveler's mean daily mileage (M_n) is computed by dividing annual mileage by 365.

For 76 percent of the vehicles in the sample, the mode of daily mileage is lower than the mean of daily mileage because long trips positively skew the daily miles distribution. The scale parameter of an individual's gamma distribution, β, is assumed to be the difference between M_n and M_d as in Equation 3. The distribution's shape parameter, k, is the average daily mileage divided by the scale parameter. These variables are calculated as:

$$\beta = M_n - M_d = \left(\frac{annual\ mileage}{365}\right) - (commute\ distance * 53/22) \qquad (3)$$

$$k = M_n/\beta. \qquad (4)$$

The remaining 24 percent of vehicles have $M_n < M_d$. This case implies that the vehicle is not driven every day, i.e. the driver occasionally takes another vehicle or mode to work. To account for zero-mile days, these vehicles are assumed to have a standard deviation of daily miles, σ_{DM}, of five miles (Lin et al. 2014). A new parameter for daily mean miles, M'_n, is used such that:

$$\sigma_{\mathrm{DM}} = 5 = \sqrt{M'_n\left(M'_n - M_d\right)} \qquad (5)$$

$$M_n = (1 - \rho)M'_n\ , \qquad (6)$$

where ρ is the share of zero-mile days (note: for the 76 percent of the vehicles where $M_d < M_n$, this share is 0 percent). For the second group of vehicles, the parameters k and β are defined as above, but M'_n is replaced for M_n. Using Equations 3 through 6, the probability density function that vehicle i travels x miles per day ($P_i(x)$) is:

$$P_i(x) = \frac{1}{\beta^k \gamma(k)} (x^{k-1} \exp\left(-\frac{x}{\beta}\right)) \text{ for } k, \beta > 0 \quad (7)$$

where γ is the gamma function.

2.3 Estimating Impact of Inconvenience Days

Figure 1 shows examples of gamma distributions for two individuals – one with high daily mileage and one with low daily mileage. Graphically, these daily mileage distributions above can be represented as person-level probability distributions. As an example, if Person A in Figure 1 is willing to accept one day per year in which his or her range preference cannot be met (i.e., one day of inconvenience out of 365), a 150-mile range BEV will satisfy all daily travel distances (i.e., 1/365 or 0.3 percent). Person B, on the other hand, has a flatter and longer-tailed distribution, meaning that 200 miles would satisfy all but five days of driving per year. Because the number of inconvenienced days a driver is willing to accept is unknown without observational data, this paper examines a spectrum of inconvenience days—1, 2, 3, 4, 5, 10, and 25 days per year, matching those in previous analyses (Peterson et al., 2014).

INSERT FIGURE 1 HERE

Person-level probability distributions can be aggregated from all of the 24,134 drivers into a single, cumulative distribution function (CDF) (Figure 2). To do this aggregation, each driver's PDF is examined to determine his or her maximum daily mileage at a given number of inconvenience days – i.e., seven maximum daily mileages for each driver (i.e., 1, 2, 3, 4, 5, 10, and 25). The CDFs for each inconvenience day curve in Figure 2 are calculated by aggregating the maximum mileage for each driver. Figure 2 demonstrates that a 100-mile range BEV would satisfy the daily travel distance of 26 percent of drivers if they are willing to be inconvenienced one day per year, but 65 percent of drivers when they are willing to be inconvenienced for 25 days per year. Figure 2 also shows the daily mileage recorded for the single day of travel in the NHTS (black dashed line). This line is much higher than the maximum daily mileage lines and demonstrates that a 100-mile range BEV could satisfy over 90 percent of all drivers' range needs in the U.S. *on a given day*, but would underestimate those drivers' true range preference. This has been shown previously (e.g., Gonder et al., 2007).

INSERT FIGURE 2 HERE

All lines in Figure 2 use the same 24,134-observation sample. Tamor et al. (2013) estimate a similar figure in their analysis of Minnesota GPS data, which matches the Figure 2 line for 25 days of inconvenience per year, but is below Figure 2's one day of inconvenience per year. Here, this paper assumes all FCEVs have a 300-mile range. Thus, only a minority of drivers (less than 15 percent) cannot meet all their range requirements, for 1 through 25 days of inconvenience.

Each CDF in Figure 2 can also be disaggregated by vehicle size class. Doing so allows estimation of the fraction of the vehicle fleet across 77 size class-range segments, as shown in Table 2. This figure shows the fraction of U.S. LDV sales for each range and size class segment, for one day of inconvenience. The gray “Row Total” column gives the sum of the market share for all vehicle range segments in a given size class. Similarly, the “Column Total” row gives the sum of the market share for all vehicle size classes for a given range. Varying the number of inconvenience days results in slight differences from Table 2, which are not shown for brevity.

INSERT TABLE 2 HERE

As an example interpretation of Table 2, the fraction of the new LDV fleet that are SUVs and that are driven a maximum of 150 to 200 miles per day, on all but three days per year is 6.4 percent (Table 2, row=SUV, column=150-200 Miles).

An underlying assumption in the use of inconvenience days is that drivers do not charge or refuel to extend their range on a high-mileage day. Data on early adopters of BEVs supports this assumption for BEVs. The Plug-in Electric Vehicle and Infrastructure Analysis report (INL, 2015) indicates that most BEV drivers only charge at three or fewer stations, typically at home or work. Overall, 84 percent of charging is performed at home. During weekdays, those with the option to recharge at home or work use these two options 97 percent of the time. During weekends, 92 percent of charging is done at home or work. Further, even in BEVs with DC fast charging capability, only 8 percent of charging events are with DC fast charging. Finally, BEV owners charge an average of 1.1 times per day on days when the BEV was driven (INL, 2015).

To account for the impact of inconvenience days in the TCO analysis, the inconvenience is converted to a cost penalty using the average cost of renting a car for rural, urban, and suburban drivers, assumed to be $41, $45, and $37 per day, respectively. This amount would presumably include the cost of vehicle rental and insurance. A time cost of $30 is added to account for the time to book the rental and travel to the rental agency. This penalty is converted to a cost per mile by dividing the daily rental cost by the assumed miles driven per year and discounting at 7 percent per year for five years (assuming resale after five years).

The above assumptions imply one day of inconvenience per year over five years has a penalty of $0.02 per mile, while 25 days of inconvenience per year over five years has a penalty of $0.57 per mile. These cost penalties are applied only to one-vehicle households – disaggregated by vehicle size class – since multi-vehicle households can replace their BEV with an ICEV on high-mileage days. The vehicle-swapping assumption substantially reduces the inconvenience penalty to $0.002 to $0.08 per mile for 1 and 25 days of inconvenience, respectively, averaged across all vehicle classes. One important note on this paper’s methodology is that a given driver's required

BEV range will decrease as the number of inconvenienced days increases. For example, in Figure 1, Person A would need a 150-mile BEV if he or she accepts one day of inconvenience per year, but only a 100-mile BEV if he or she accepts five days of inconvenience per year.

3. Results

Figure 3 shows the difference in TCO for FCEVs minus BEVs for 2020 and 2040 for 11 vehicle size classes and seven vehicle ranges for three days of inconvenience. Figure A-5 in the Appendix shows the same as Figure 3, but for all analysis years: 2020, 2025, 2030, 2035, and 2040. The breakdown of costs by component (e.g., battery, motor, etc.) is shown for five different size classes in Figure A-6 in the Appendix. The heat maps in Figure 3 convey a number of important insights. First, as expected, the difference in TCO between BEVs and FCEVs decreases over time. Second, the relative change in costs over time slightly favors FCEVs, such that by 2040 most of the high-mileage vehicle segments are cheaper for FCEVs. Third, higher range BEVs are less cost-competitive with FCEVs.

INSERT FIGURE 3 HERE

Figure 4 shows the total fraction of the LDV fleet that is competitive for FCEVs from 2020 to 2040 for 1, 2, 3, 4, 5, 10, and 25 days of inconvenience. These fractions are calculated by summing the portion of the LDV market matrix (e.g., Table 2) that has lower TCO for FCEVs than BEV, for each inconvenience day. For three days of inconvenience, the matrix in Table 2 is used. Other days of inconvenience are not shown but are available upon request. Figure 4 shows that there is a general trend towards greater FCEV competitiveness as time progresses, mainly driven by cost reductions in FCEV components and by the reduction of detour trips after 2030.

INSERT FIGURE 4 HERE

The Figure illustrates that adding the inconvenience penalties has a mixed impact on the competitiveness of FCEVs versus BEVs. In 2020 and 2025, as the number of assumed inconvenience days increases, the size of the LDV market competitive for FCEVs decreases. This result is driven by how inconvenience is defined – i.e., “the maximum daily mileage in a year required by drivers on all but a given number of days.” Thus, the more inconvenience days, the lower the maximum daily mileage in a year. This, in turn, pushes the CDF curves in Figure 2 left, towards lower-range vehicles (i.e., towards BEV-competitive segments). In the most sensitive year, 2025, varying the number of inconvenience days from 1 to 25 days results in a 25 percent difference in competitive market share for FCEVs. In later years (2030 to 2040), the impact of BEV drivers paying for rental cars on their high mileage days results in greater FCEV competitiveness on high number of inconvenience days.

4. Sensitivity Analysis

A sensitivity analysis is performed to understand the impact of changing individual parameters of the TCO model on the relative costs of BEVs and FCEVs, and ultimately on the fraction of the LDV fleet that is cost competitive for one vehicle type or the other. The TCO model used in this paper assumes that by 2040 aggressive cost targets have been met. The assumptions for each parameter is stated below for both the base case and the sensitivity analysis cases.

Figure 5 gives the resulting change in the fraction of LDV sales that are competitive for FCEVs in 2040 for a range of assumptions. The figure uses the three inconvenience days curve which, in the base case, results in 74 percent of the LDV market being economically favorable for FCEVs. Table 3 describes how parameters in the analysis were varied to produce Figure 5.

INSERT FIGURE 5

INSERT TABLE 3

Figure 5 demonstrates a range of sensitivities across different input parameters. Bars to the left of center indicate a decreasing share of the 2040 LDV market that is competitive for FCEVs, whereas bars to the right of center indicate an increasing share that is competitive for FCEVs. Unsurprisingly, vehicle components that constitute a large overall share of the TCO of each of the vehicles (e.g., hydrogen fuel) have an overall important role in determining the share of the market that is competitive for FCEVs. The analysis also suggests that other parameters besides hydrogen fuel cost have a comparatively smaller impact on the overall size of segmented markets for BEVs and FCEVs. Achieving hydrogen fuel cost reductions is thus critical to the overall success of FCEVs in the marketplace. Other years of analysis are not shown, but show similar conclusions.

5. Discussion

5.1 Market Segmentation Results

Although future vehicle costs and technology advancement are uncertain, this paper's investigation into the market segmentation of FCEVs and BEVs suggests a number of potentially useful observations for policymakers and planners. First, the paper finds that both FCEVs and BEVs have market segments with sometimes substantial cost advantages over one another, particularly in early years. For example, a BEV-50 pickup truck in 2020 is more than $1.00 per mile cheaper than an equivalent FCEV. Alternatively, a BEV-300 passenger van in 2020 is about $0.45 per mile more expensive than an equivalent FCEV. Earlier investigations considered the technoeconomic performance and optimality of BEVs and FCEVs (e.g, Delucchi and Lipman, 2001; Lin et al, 2014; Ogden et al, 2004). Though the scope of these analyses differs from this current paper, the analysis agrees with others (e.g., Lin et al. (2014)) that shorter range BEVs are more attractive from a cost standpoint than longer range BEVs.

Second, the paper finds that the number of FCEV-competitive segments grow over time as the relative TCOs become more favorable for FCEVs and the impact of detour trips decreases. By 2040, for all vehicle classes except pickup trucks, all but the 50- and 100-mile range segments of the 77 range-size class segments are cheaper for FCEVs than BEVs. The analysis relies on the assumption that the US DOE cost targets are met for both FCEV and BEV components. Whether such an assumption will hold true or whether each of the cost targets are equally likely to be reached or exceeded is not examined here. This analysis should therefore be updated as a clearer picture of fuel cell stack, hydrogen tank, hydrogen fuel and BEV battery pack costs emerges. The sensitivity analysis suggests that the hydrogen dispensing cost, in particular, could shift the results and therefore deserves closer inspection.

Third, the acceptable number of inconvenience days for potential BEV owners plays an important role in the results, as show in the sensitivity analysis. The size of the FCEV-competitive segments changes by as much as 25 percent between 1 and 25 inconvenience days per year (Figure 4, year 2025). A related insight is that more days of assumed inconvenience results in a shift in the LDV market towards lower range vehicles. This, in turn, favors BEVs since they are more cost competitive at lower ranges. The magnitude of the effect of inconvenience days on the FCEV-competitive market share suggests a need for research into estimating individual driver's cost penalties for inconvenience.

Finally, the results suggest an important inflection point in costs occurs around 2030 when the assumed cumulative number of FCEVs sold passes one million. As shown in Figure 4, in 2030, FCEVs become the lower cost vehicle option in the majority of the LDV market and maintain that advantage through 2040.

5.2 Impact of Key Assumptions

Several factors contribute to uncertainty in this analysis. The paper only compares two promising powertrains with the potential to run on 100 percent renewable resources, but these powertrains compete in a larger marketplace, including plug-in hybrid electric vehicles, plug-in hybrid FCEVs, HEVs, flex-fuel vehicles, and ICEVs. Ultimately, FCEVs and BEVs are chosen for this analysis because of their promise to deliver deep cuts to lifecycle, cradle-to-grave greenhouse gas emissions (ANL, 2016a), while also possessing the technical potential to displace all of the U.S. petroleum demand for transportation if sourced from wind or solar pathways (LLNL, 2017; Ruth, 2017).

Due to the relative immaturity of FCEV and BEV technologies, the authors attempt to provide equally optimistic component costs for BEVs and FCEVs by using powertrain costs from *Autonomie*. The costs for fuel cells, hydrogen tanks, balance of plant components are derived from US DOE estimates, and battery packs for BEVs from major battery manufacturers (ANL, 2016c). In the case of FCEVs, further attempts are made to increase component costs due to the low volume of FCEV sales to date, as described above in 2.1.3.

The paper focuses on only three factors that influence vehicle purchase decisions: daily driving distributions, size class, and TCO. Many other relevant variables could be used to segment the light-duty vehicle market, such as house-level or travel-related variables. Additionally, a growing line of research underscores the importance of non-monetary factors such as symbolic and functional benefits of vehicles to consumers (Axsen et al., 2013).

Estimates of the potential size of the BEV and FCEV markets assume that PDFs for daily VMT will be static into the future. In reality, these PDFs could change for a variety of reasons, such increased penetration of autonomous vehicles (Shin et al., 2015). However, current investigations in the expected shift in VMT from autonomous vehicles suggest VMT could increase or decrease (see, e.g., Stephens et al., 2016b), and therefore are not incorporated into the authors' analytical framework. The authors propose that this be revisited in future studies.

Another potential uncertainty is depreciation rate, which impacts the resale value after the assumed 5-year ownership period. Today's BEV experience a high depreciation rate (Zhou et al., 2016). While this paper uses a constant depreciation rate for all vehicles, actual depreciation rates vary by vehicle powertrain, model, make, class, fuel cost and other factors (National Automobile Dealers Association, 2016). The relative infancy of the FCEV and BEV markets makes the estimated depreciation rate used in this analysis worth refining in future analyses.

Finally, the paper does not directly address the "valley of death" that exists in early years of hydrogen FCEV deployment – i.e., the market entry barrier facing new technologies that must scale up production in order to compete economically. In particular, hydrogen infrastructure and vehicle subsidies are not included in the TCO calculations. While infrastructure and vehicles subsidies also exist for BEVs, the majority of US vehicles at least have access to Level 1 charging – Axsen and Kurani (2012) estimated 25 percent of US vehicles park overnight within 25 feet of a usable electrical outlet for Level 1 charging. By some estimates (Melania et al., 2017), as many as many as 3,300 stations are needed to support an FCEV population of 4.5 million in 2035. California and the US. Northeast states are expanding the number of refueling stations, but still only have 25 stations currently open to the public at the time of writing (CARB, 2015; California Fuel Cells Partnership, 2017). However, as demonstrated by NRC (2013), only the first wave of stations and vehicles are expected to need subsidies. Ogden et al. (2014) estimate that as little as $100-$200 million of public investment is needed to build 100 hydrogen refueling stations for a vehicle population of around 50,000 FCEVs. The authors estimate this initial investment is sufficient to drive down costs to be similar to gasoline ICEVs.

6. Conclusions and Future Work

This study analyzed the relative competitiveness of FCEVs and BEVs on a TCO basis. The TCO was calculated using *Autonomie*, assuming that US DOE cost targets were met for both FCEVs and BEVs. Using survey data and statistical methods, distributions of vehicle miles traveled per person, per day were constructed. BEVs with ranges shorter than the maximum vehicle miles traveled per day incurred TCO penalties through the introduction of an additional cost of car rental.

The paper finds that BEVs maintain a strong cost advantage over FCEVs today, but the cost advantage quickly diminishes by 2030, driven largely by the sharp cost reductions in FCEVs relative to those of BEVs. This is modeled to occur as greater numbers of FCEVs are deployed and the presumed early-stage technology learning occurs for FCEVs as it has for BEVs. By 2030, the LDV market is split, with roughly one half of segments being competitive for FCEVs and the other half for BEVs. As FCEVs continue to decline in cost, they become the lower cost option in the majority of vehicle segments. A sensitivity analysis was performed on the results, and shows that varying the projected hydrogen fuel cost, as well as the fuel cell drivetrain components had a large impact on the size of the total LDV market that was competitive for FCEVs. Varying battery cost and the total years of vehicle ownership had a smaller yet still significant effect on the FCEV-competitive LDV market size.

Lastly, the article shows that certain vehicle segments appear to be better suited for one powertrain than another – in particular, larger vehicles like passenger vans and sports-utility vehicles (SUVs) appear to have a relative cost advantage for FCEVs over BEVs. Similarly, smaller size classes like mini-compacts, compacts, and midsize sedans appear to be the strongest economic performers for BEVs. Thus, this paper projects the existence of an LDV market that allows for coexistence of both FCEVs and BEVs.

Future studies could validate and update the conclusions of this work as real-world data on FCEV and BEV costs and driving behavior becomes available. These data should be used to reassess the potential sizes of these market segments. Future market segmentation studies should also focus on better understanding the extent to which vehicle owners are willing to accept range inconvenience. Additionally, to assist policy makers in prioritizing research and development funding, there is a need to repeat this analysis for other applications such as medium and heavy-duty trucks, back-up power, and material handling equipment.

Acknowledgements

The authors would like to thank Tien Nguyen and Rachel Nealer for assisting in performing this study. This research was supported in part by the Department of Energy (DOE) Office of the Secretary administered by the Oak Ridge Institute for Science and Education (ORISE) for the DOE. ORISE is managed by Oak Ridge Associated Universities (ORAU) under DOE contract number DE-AC05-06OR23100. We also appreciate the insightful comments of four annoymous reviewers. All opinions expressed in this paper are the author's and do not necessarily reflect the policies and views of DOE, ORAU, or ORISE.

The authors declare no conflicts of interest.

Glossary of Terms

TCO – Total Cost of Ownership of a Vehicle, on a Discounted Cost per Mile Basis
FCEV – Fuel Cell Electric Vehicle
BEV – Battery Electric Vehicle
HEV – Hybrid Electric Vehicle
PHEV – Plug-In Hybrid Electric Vehicle
ICEV – Internal Combustion Engine Vehicle
LDV – Light Duty Vehicle
Autonomie – Vehicle Cost and Fuel Use per Mile Simulation Software developed by Argonne National Laboratory
MA^3T – Market Acceptance of Advanced Automotive Technologies Vehicle Consumer Choice Model developed by Oak Ridge National Laboratory
NHTS – 2009 Department of Transportation National Household Travel Survey
CDF – Cumulative Distribution Function
ANL – Argonne National Laboratory
US DOE – United States Department of Energy
INL – Idaho National Laboratory
LLNL – Lawrence Livermore National Laboratory
NREL – National Renewable Energy Laboratory

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Figures for:
Relative Economic Competitiveness of Light-Duty
Battery Electric and Fuel Cell Electric Vehicles

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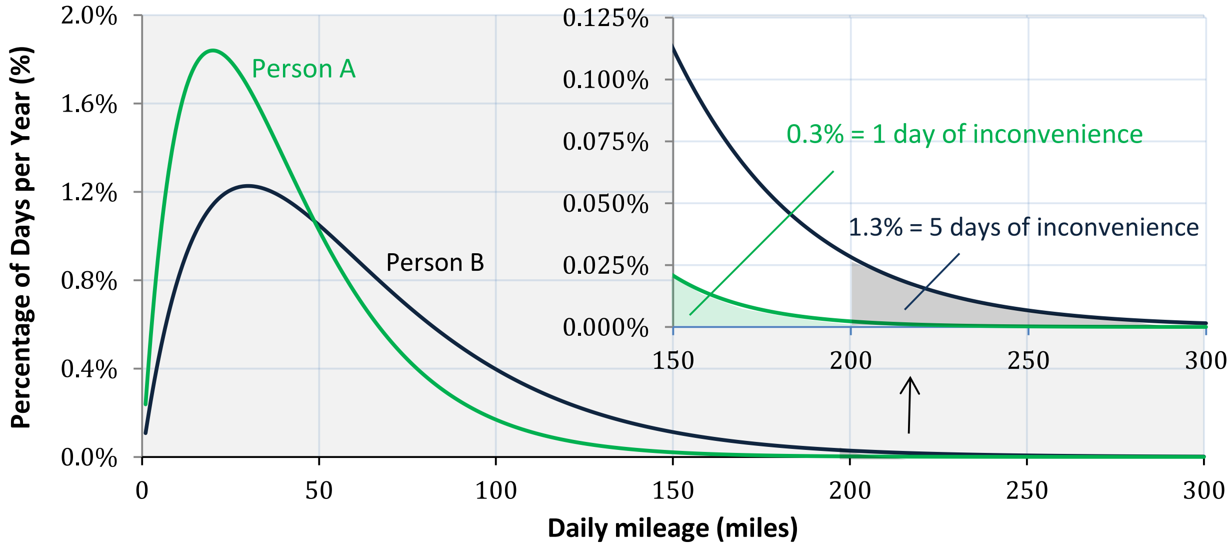

Figure 1: Frequency distribution of two example individuals of daily miles driven over an entire year. Person A (green) has a higher number of short-mileage days than Person B (black). A 150-mile range BEV would satisfy Person A on all but 1 of 365 days per year, whereas a 200-mile range BEV would satisfy Person B all but 5 of 365 days per year.

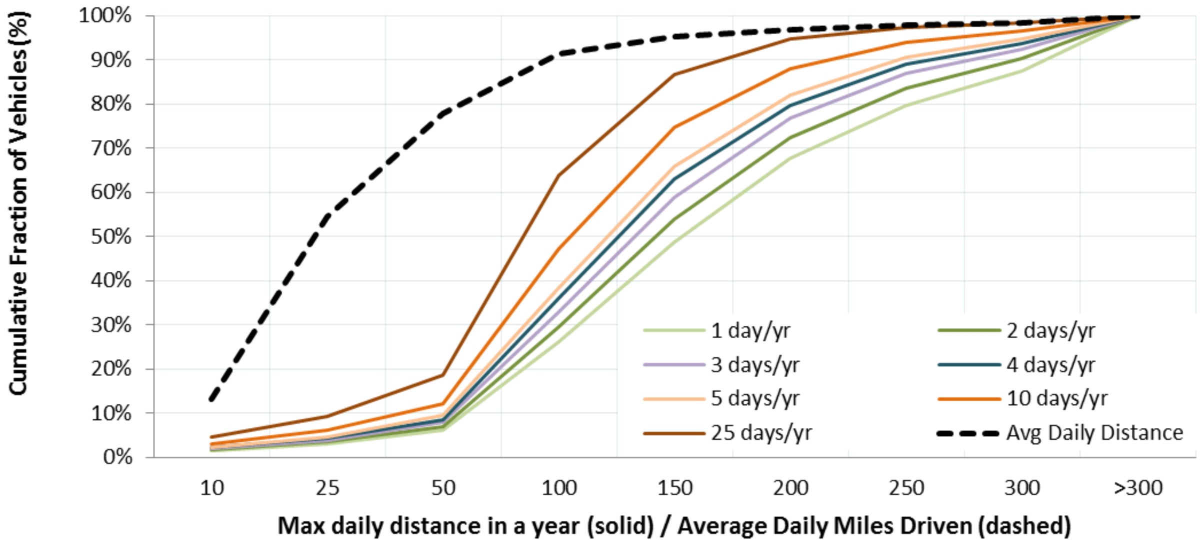

Figure 2: Cumulative frequency distribution of maximum daily mileage, by number of days of inconvenience. Dashed black line is the cumulative frequency distribution of daily average distance (i.e., total mileage reported in 2009 NHTS for respondent's travel day).

Year: 2020

FCEV minus BEV-X Cost

	50 Miles	100 Miles	150 Miles	200 Miles	250 Miles	300 Miles	350 Miles
Two-Seaters	$0.54	$0.40	$0.27	$0.13	$0.00	-$0.13	-$0.27
Minicompacts	$0.74	$0.63	$0.53	$0.42	$0.32	$0.21	$0.11
Subcompacts	$0.70	$0.59	$0.48	$0.37	$0.26	$0.15	$0.04
Compacts	$0.50	$0.39	$0.28	$0.17	$0.07	-$0.04	-$0.15
Midsize Cars	$0.59	$0.46	$0.33	$0.21	$0.08	-$0.05	-$0.17
Large Cars	$0.55	$0.43	$0.32	$0.20	$0.08	-$0.04	-$0.15
Small Station Wagons	$0.65	$0.51	$0.37	$0.23	$0.08	-$0.06	-$0.20
Pass Van	$0.38	$0.23	$0.07	-$0.08	-$0.24	-$0.39	-$0.55
SUV	$0.66	$0.47	$0.28	$0.09	-$0.10	-$0.29	-$0.48
Std Pickup	$0.94	$0.82	$0.71	$0.59	$0.47	$0.36	$0.24
Small Pickup	$0.47	$0.32	$0.18	$0.04	-$0.11	-$0.25	-$0.39

Year: 2040

FCEV minus BEV-X Cost

	50 Miles	100 Miles	150 Miles	200 Miles	250 Miles	300 Miles	350 Miles
Two-Seaters	$0.05	$0.01	-$0.03	-$0.07	-$0.11	-$0.15	-$0.19
Minicompacts	$0.05	$0.02	-$0.01	-$0.04	-$0.07	-$0.10	-$0.13
Subcompacts	$0.05	$0.02	-$0.01	-$0.04	-$0.07	-$0.11	-$0.14
Compacts	$0.04	$0.01	-$0.02	-$0.05	-$0.09	-$0.12	-$0.15
Midsize Cars	$0.05	$0.01	-$0.03	-$0.06	-$0.10	-$0.13	-$0.17
Large Cars	$0.04	$0.01	-$0.02	-$0.06	-$0.09	-$0.12	-$0.16
Small Station Wagons	$0.05	$0.01	-$0.03	-$0.07	-$0.11	-$0.15	-$0.19
Pass Van	$0.03	-$0.01	-$0.06	-$0.11	-$0.15	-$0.20	-$0.24
SUV	$0.03	-$0.02	-$0.08	-$0.14	-$0.19	-$0.25	-$0.30
Std Pickup	$0.14	$0.11	$0.07	$0.04	$0.01	-$0.03	-$0.06
Small Pickup	$0.06	$0.02	-$0.02	-$0.07	-$0.11	-$0.15	-$0.19

Figure 3: Difference in TCO of FCEV and BEV ($Cost_{FCEV}$ - $Cost_{BEV}$) for 2020 and 2040. Red indicates favorable TCO for BEVs. Green indicates favorable TCO for FCEVs.

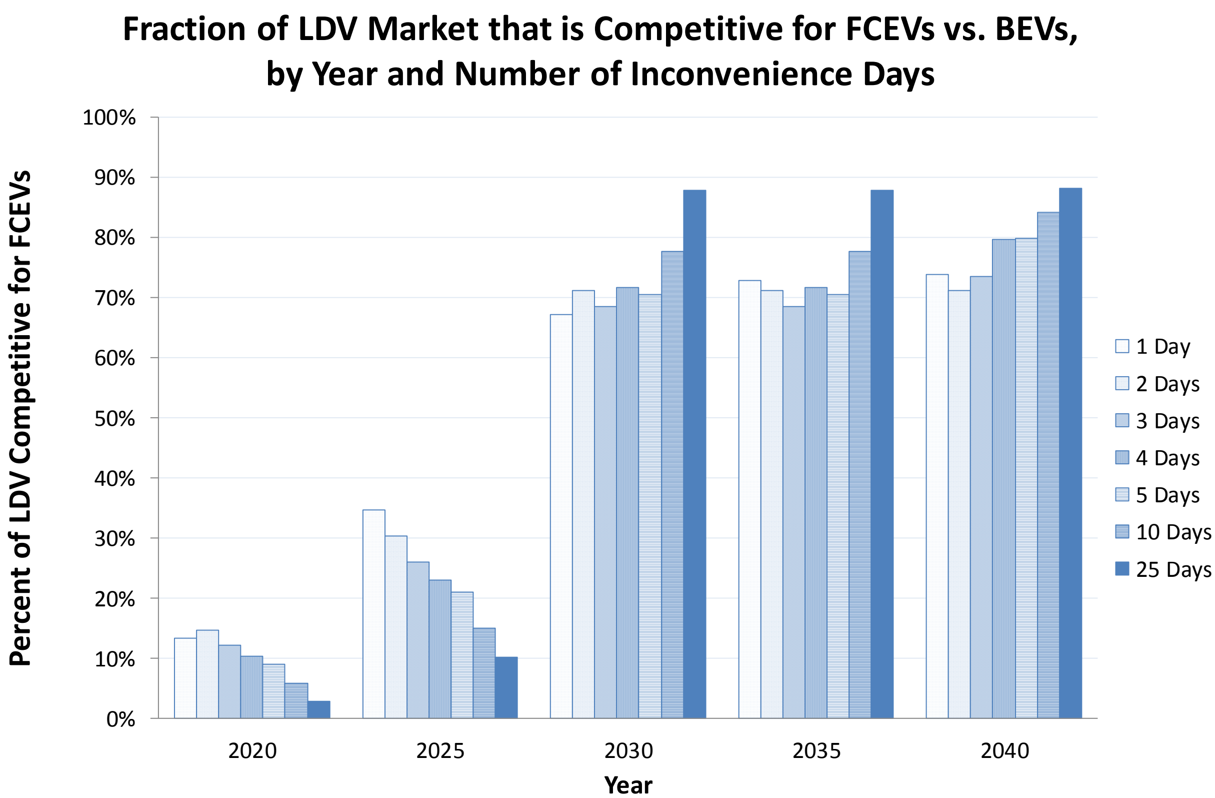

Figure 4. Fraction of LDV fleet that is cost competitive for FCEVs (BEVs) as a function of days of inconvenience per year. Inconvenience penalty is assessed to vehicles that do not belong to a multi-vehicle household.

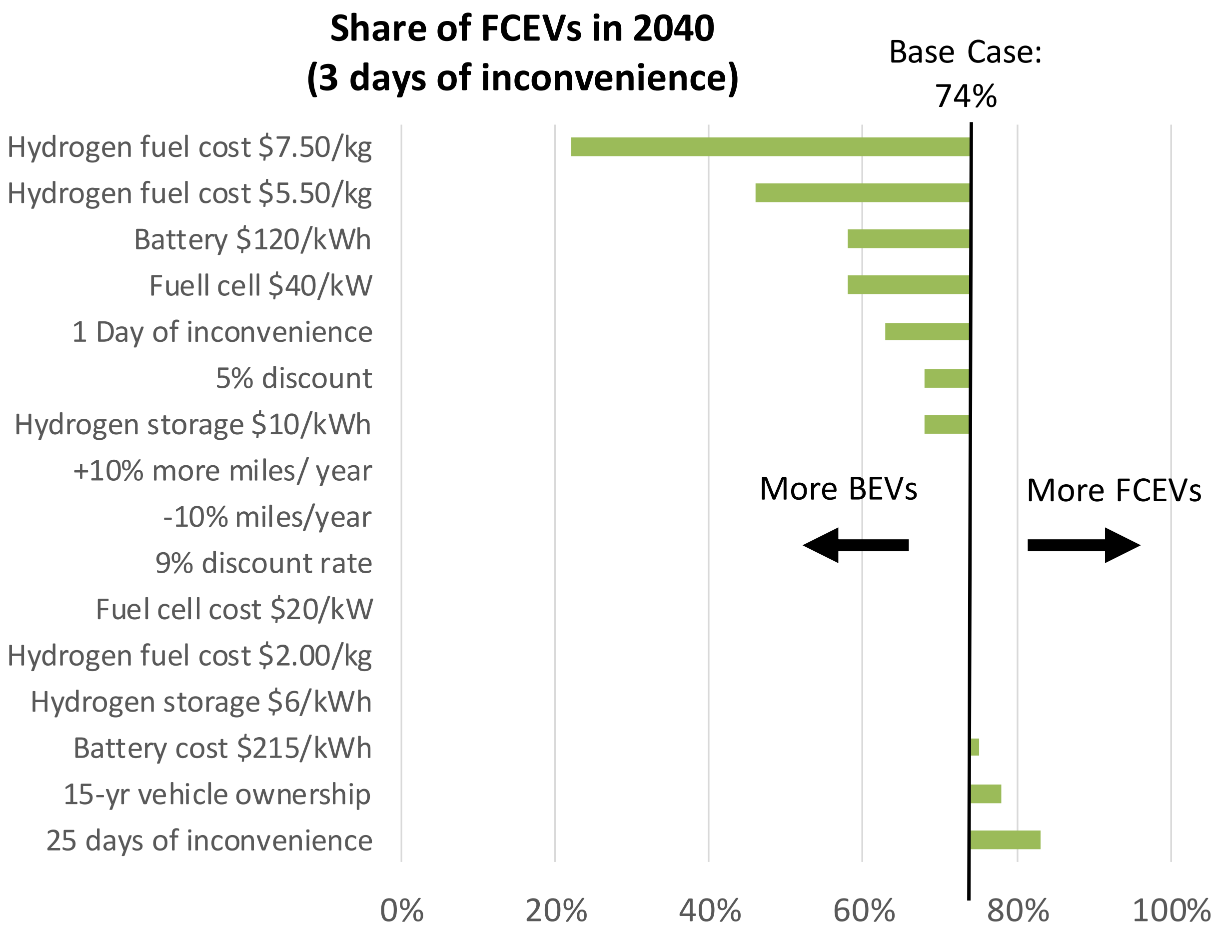

Figure 5. Sensitivity analysis of input parameters for <u>three</u> days of inconvenience in 2040. Base values of each variable are given in Table 3.

Tables for:
Relative Economic Competitiveness of Light-Duty Battery Electric and Fuel Cell Electric Vehicles

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Table 1. Assumed market adoption of FCEVs LDVs

Year	Stock of FCEVs	Fraction of LDV Market
2020	23,000	0.0%
2025	78,000	0.0%
2030	3,300,000	1.2%
2350	1,220,000	4.5%
2040	28,000,000	10.1%

Table 2: Market size of 77 market segments, assuming <u>three</u> day per year of inconvenience. Percentages shown in figure refer to the fraction of LDV fleet that drives a <u>maximum</u> of given distance in a year on all but one day per year (e.g., the fraction of SUVs that are driven a maximum of 150-200 miles per year is 6.4% of all LDVs). Percentages in white cells are summed in shaded cells.

	< 50 Miles	50-100 Miles	100-150 Miles	150-200 Miles	200-250 Miles	250-300 Miles	300+ Miles	Sum
Two-Seaters	0.1%	0.2%	0.2%	0.2%	0.1%	0.0%	0.0%	**0.7%**
Minicompacts	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.2%**
Subcompacts	0.5%	1.4%	1.3%	0.9%	0.6%	0.2%	0.4%	**5.2%**
Compacts	1.5%	4.9%	4.5%	3.1%	1.8%	1.1%	1.4%	**18.5%**
Midsize Cars	1.6%	4.8%	5.0%	3.5%	1.5%	1.0%	1.3%	**18.7%**
Large Cars	0.8%	2.3%	2.3%	1.6%	1.0%	0.5%	0.8%	**9.1%**
Small Station Wagons	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.1%**
Passenger Van	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	**0.0%**

Sports Utility Vehicle	2.5%	8.2%	9.1%	6.4%	3.7%	2.0%	2.7%	**34.5%**
Standard Pickup	0.8%	3.2%	3.4%	2.1%	1.2%	0.7%	1.1%	**12.4%**
Small Pickup	0.0%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	**0.5%**
Sum	**7.8%**	**25.1%**	**26.0%**	**17.9%**	**10.0%**	**5.5%**	**7.7%**	**100%**

Table 3: Parameters varied for sensitivity analysis shown in Figure 5.

Parameter	**Base case assumption**	**Sensitivity analysis assumption**
Hydrogen fuel cost	Hydrogen price at the pump declines from $13 per kg in 2015 to $2.50 per kg in 2040	Hydrogen price at the pump declines from $13 per kg in 2015 to $2.00, $5.50, and $7.50 per kg in 2040
Fuel cell cost	Fuel cell costs decline from $280 per kW in 2015 (low volume conservative cost estimate) to $30 per kW in 2040	Fuel cell costs decline from $280 per kW in 2015 to $20 and $40 per kW in 2040
Hydrogen storage	Gaseous storage tank costs decline from $33 per kWh in 2015 to $8 per kWh in 2040	Gaseous storage tank costs decline from $33 per kWh in 2015 to between $6 and $10 per kWh in 2040
Battery cost	Battery costs decline from $360 per kWh in 2015 to $165 per kWh in 2040	Battery costs decline from $360 per kWh in 2015 to between $120 and $215 per kWh in 2040
Annual miles	Vehicle driven 14,231 miles per year in first year of ownership, declining to 13,028 by year five	Vehicle driven 10 percent more and less than base case
Discount rate	7 percent	5 to 9 percent discount
Vehicle ownership term	Vehicle is sold after five-year ownership for 38.2 percent of purchase price.	Vehicle is kept for its entire 15-year lifespan. Costs are annualized over 15 years. No resale value.