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History v. Simulation: An Analysis of the Drivers of Alternative Energy Vehicle Sales

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ABSTRACT

Simulations of the US light duty vehicle stock help policy makers, investors, and auto manufacturers make informed decisions to influence the future of the stock and its associated green house gas emissions. Such simulations require an underlying framework that captures the key elements of consumer purchasing decisions, which can be uncertain. This uncertainty in a simulation's logic is usually convolved with uncertainty in the underlying assumptions about the futures of energy prices and technology innovation and availability. By comparing simulated alternative energy vehicle (AEV) sales to historical sales data, one can assess the simulation's ability to capture the dynamics of consumer choice, independent of many of those underlying uncertainties, thereby determining the factors that most strongly impact sales. The market for diesel vehicles, hybrid electric vehicles, and to a lesser extent plug-in hybrid electric vehicles and all-electric vehicles, has now matured sufficiently to make such a study possible. In this work, we measure the results of the Sandia ParaChoice model under a variety of input assumptions against historical sales data. We observe that (1) the underlying simulation logic is sound, capturing key drivers of consumer choice, (2) AEV model availability has a significant impact on sales, and (3) AEV consumers are very likely aware of purchasing incentives and factoring those incentives into their purchasing decisions.

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INTRODUCTION

After a hundred year losing battle against gasoline powered vehicles, alternative energy vehicles (AEVs) have begun to re-gain ground in the US light duty vehicle (LDV) market. Starting with the model year 2000 Honda Insight and Toyota Prius, hybrid electric vehicles (HEVs) started their re-entry into the US market. After an initial failure to re-introduce all-electric or battery electric vehicles (BEVs) to the US market in the late 1990s [1], auto-manufacturers are starting to make headway with BEVs as well, with more than 35,000 sold in the first half of 2015. Plug-in hybrid electric vehicle (PHEV) sales passed 18,000 for 2015 this past June, and diesel vehicle sales passed 89,000 [2]. HEVs, PHEVs, BEVs, and diesel vehicles currently comprise nearly 4% of new US LDV sales.

Previous studies [3, 4, 5, 6, 7] have used consumer choice models such as the Transitional Alternative Fuels and Vehicles (TAFV) model [8], Market Acceptance of Advanced Automotive Technologies (MA^3T) model [9], Light Vehicle Consumer Choice (LVChoice) model [10], Light-duty Alternative Vehicle Energy Transitions (LAVE-Trans) model [11], and ParaChoice [12, 13] to project vehicle sales and their corresponding emissions out through 2050. These studies have typically utilized best available assumptions for commodity prices and technological advances [14, 15, 16]. Recent studies have parameterized over these variables to probe the response of the LDV stock and emissions to changes in the input parameters, and thus to analyze the sensitivity of the LDV fleet to input conditions and identify technology and policy levers that can reduce green house gas emissions and petroleum consumption [12, 13, 17].

While it is impossible to accurately predict LDV sales decades into the future, one can compare simulations to historical data, for which commodity prices and the pace of technology innovation are known. Deviations between the simulated and historical sales data can demonstrate the sensitivities of the simulation to input assumptions and also help identify whether the logic underlying the simulation appropriately captures the dynamics of the market and consumer choice. The market for diesel vehicles, HEVs, and to a lesser extent PHEVs and BEVs, has now matured sufficiently to make such a study possible. Therefore, this study compares the simulated sales generated by the Sandia ParaChoice model to historical AEV sales data from *HybridCARS* [18, 19] for 2010-2015.[1] By varying the underlying model assumptions, we seek to understand which factors have significant influence on consumer choice.

[1]We focus on the ParaChoice model as opposed to the various models listed above as the ParaChoice model was developed in house at Sandia National Laboratories and thus we have access to the source code to make the modifications necessary to perform this study. While the ParaChoice model shares structural similarities with many of these models, conclusions drawn here for ParaChoice may or may not be applicable to other models depending on each model's specific assumptions.

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The ParaChoice model simulates the dynamic interaction and evolution of the LDV stock, fuel production, and energy supplies through 2050 [12]. The simulation occupies a system-level analysis layer with input from other US Department of Energy models to explore the uncertainty and trade space (with 10,000s of model runs) that is not accessible in individual scenario-focused studies.

ParaChoice models dynamics and competition among LDV powertrains and fuels using regional-level feedback loops from vehicle use to energy source. This enables identification of conditions required to reach performance goals, and sensitivity and tradeoff analyses between technology investments, market incentives, and modeling uncertainty. The ParaChoice model currently includes twenty different drivetrains, including a range of spark ignition and compression ignition (hybrid and non-hybrid), natural gas, battery electric, plug-in hybrid, and fuel cell electric vehicles.

In this work we look more closely at the simulation's ability to accurately capture the dynamics of historical AEV sales from 2010-2015. Rather than parameterizing over uncertain futures, this study uses historical values for commodity prices and state of technology. The simulated vehicle stock is initialized to the known US LDV stock composition at the end of 2009, and the simulation calculates sales by quarter to 2015. We then re-run the simulation using different underlying assumptions for vehicle model availability and federal and state purchasing incentives, factors which significantly influence vehicle sales. We compare the simulated and historical sales for diesels, HEVs, PHEVs, and BEVs, and thereby probe the underlying simulation logic and the drivers of consumer choice.

MODEL DESCRIPTION

The ParaChoice model has been described in depth in previous works [12, 13, 17]. We devote this section to highlighting those model assumptions most relevant to this analysis.

1. Energy and fuel prices for 2010-2015 are taken from previous and current publications of The US Department of Energy's Annual Energy Outlook reference case (AEO) [14, 20, 21]. Prices for each simulation time step are interpolated linearly between yearly reported average values; quarterly energy price fluctuations are not captured.
2. The initial composition of the vehicle stock is taken from the US Department of Transportation Federal Highway Administration 2009 State Motor Vehicle Registrations [22]. Model availability by powertrain is compiled by SRA International, Inc. from data from R.L. Polk and Co. [23]. For this study, we only use 2009 registration numbers and AEV registration fractions for model years prior to 2010. We do not use any stock or sales data from 2010 forward in our simulations.
3. Initial vehicles in the stock are assigned fuel efficiency based on historical data [24]. For 2010 forward, vehicle efficiency data and technology prices for all powertrains and all fuel sources are derived from Autonomie 2015 [15]. Plotkin and Stephens [25] demonstrate that there exists a 3-8 year lag between a major vehicle technology reaching commercialization goals in a lab and its low volume introduction into the market. Others [26, 27] have noted this 'deployment lag' as well, though the time-to-market in these works is somewhat convolved with the time to significant market penetration. Given this lag between demonstrated and commercialized technology, we use Autonomie 2015 [15] price and efficiency data for 2010 for all years between 2010 and 2015. We note that this is an optimistic assumption for the efficiency and price of new technologies in 2010. Price data compared to conventional vehicles are shown in table 2.
4. Consumers are assumed to be rational and make purchases based on total vehicle cost, which includes technology cost as well as fuel prices and costs of inconvenience (e.g. effective cost of sparse fueling infrastructure). As these costs vary by location, driver characteristics, and vehicle technology, consumers and vehicles are segmented by state, population density, dwelling type, driving intensity, vehicle size, and powertrain in the choice modeling for vehicle sales. For all other consumer and vehicle characteristics, we assume an 'average' consumer; luxury vehicle premiums are not included and consumers are not segmented by income or 'technology attitude' [9] (e.g. early adopter v. early majority [28, 29]).
5. The ParaChoice model does not simulate seasonal buying trends. Figure 1a shows that total vehicle sales tend to follow an annual cycle, with sales tending to peak in the spring and summer and drop in the winter months. This is not a recent trend [30]. Because the ParaChoice model is designed to capture the vehicle stock many years or decades into the future, and seasonal effects average out, we do not capture seasonal sales variability in the model. Moreover, the consumer choice model predicts sales fractions by powertrain, which is not affected by total sales; it is only after the choice calculation that sales fractions are converted to numbers of sales via multiplication with a total sales number that scales with projected population growth.

   In order to avoid discrepancies between the simulated and historical AEV sales caused by seasonal purchasing trends, we compare simulated and historical sales fractions of AEVs. By comparing sales fractions rather than total sales, we also nullify differences in the sales projections that arise simply from incorrect assumptions for total vehicle sales.
6. The baseline simulation assumes an S-Curve growth in model availability, starting from a pre-determined introductory year for the technology. This is consistent with historical deployment of vehicle technology [26]. In this work, we consider model availability in three ways.
   a. Baseline case S-Curve model availability:

      Here we assume that model availability growth κ for each powertrain n follows

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$$\kappa_n = \frac{k_1}{1 + 1000 \exp\left[k_2 (t - m_n^0)\right]}$$
$$k_1 = \begin{cases} 1, & t \geq m_n^0 \\ 0, & t < m_n^0 \end{cases}; \qquad k_2 = -0.3/\text{year} \tag{1}$$

where t is time and m^0 is the start year parameter for a given powertrain. This start year parameter is set to the year of the most recent major market introduction in the US.[2] Values for m_0 for the various powertrains are given in table 3.

b. Historical model availability:

Just as we know the actual commodity prices from 2010-2015 and use them in this study, we know the actual number of models available in each vehicle size class over the time period of interest. We explore the effects of using historical model availability, inferred from the DOE Fuel Economy Guide [31] and the *HybridCARS* monthly Dashboards [18, 19]. The makes and models for diesel vehicles, hybrids, PHEVs and BEVs used in this study can be found in tables 6, 7, 8, and 9 in the appendix. Model availability by year for these AEVs are shown in figure 2. We approximate a con-stant model availability for each year using the vehicle model year, though in actuality many models enter the market in the latter part of the year preceding the model year and stay on the market through the first months of the the year following. Additionally, we use some subjectivity to define what constitutes a unique model (e.g. combining 2WD and 4WD versions of otherwise very similar vehicles). Last, we exclude fleet and specialty vehicles, vehicles that never made it to the US market, and California compliance cars. We here define 'California cars' as vehicle models sold exclusively in California and Oregon. Often these vehicles are sold in limited numbers regardless of demand [32, 33], in order to maintain compliance with CA's zero-emission vehicle production requirements [34].

c. Non-luxury vehicles:

We also explore model availability for different upper limits on manufacturer suggested retail prices (MSRP). As stated earlier, the ParaChoice model does not segment consumers by income or technology attitude, but rather assumes an average consumer in these regards. As 98% of vehicle sales are for vehicles below $50k MSRP [35], AEV models at much higher price points may not have a significant effect on the vehicle choice criteria of the majority of consumers. We therefore explore the effects of using historical model availability including only those models which are 'non-luxury' and thus accessible to the average consumer. Since historical sales [35] show that the largest sales fractions of plug-in electric vehicles are for vehicles priced higher than $50k, we also explore setting the non-luxury price threshold to $70k, which still excludes very costly vehicles like the Ferrari LaFerrari, the Porsche 918 Spyder, and the McLaren P1, while including the sound majority of US vehicle sales.[3] See figure 1b and c for a comparison of the total hybrid and diesel vehicle sales to sales of models priced below $70k and $50k. We therefore examine model availability at price points below $70k and $50k and compare the projections of the simulation using these model availabilities to the corresponding non-luxury sales data. Vehicle prices for AEV models available between 2010 and 2015 can be found in tables 6, 7, 8, and 9, and model availability by price point is shown in figure 2.

7. The simulation does account for federal and state purchasing incentives by default. The current federal incentive for plug-in electric vehicles allows a credit of $2,500 to $7,500 for BEVs and PHEVs [34]. The value of the credit for each vehicle model scales with the battery capacity [36]. State incentives, including tax credits, home charger discounts, high occupancy vehicle lane allowances, and more, are also included in the model. In the sections on PHEVs and BEVs, we explore the effects of removing these incentives in the simulation in order to determine what impact incentives may be having on consumer purchasing decisions.

Table 1. Average imported oil prices from AEO. All prices converted to 2012 USD.

2010	2011	2012	2013	2014	2015
$79.09	$104.47	$101.11	$96.71	$86.44	$48.80

Table 2. Price premium for midsize AEVs over conventional SI vehicles, from Autonomie 2015. All prices converted to 2012 USD.

CI	HEV	PHEV10	PHEV40	BEV75[a]	BEV100
$2,623	$4,065	$4,742	$11,090	$7,565	$10,133

[a] Vehicle price inferred by scaling the BEV100 battery cost by 75%.

Table 3. US light-duty vehicle mass market introduction year for each powertrain.

Powertrain	Year
SI	1920
CI	2009[a]
HEV-SI	2000[b]

[a] Re-introduction of compact, non-luxury CIs (Volkswagen and others)
[b] Honda Insight and Toyota Prius

Powertrain	Year
PHEV10-SI	2012
PHEV40-SI	2011
BEV75	2011
BEV100	2011
BEV150	2012[c]
BEV225	2012[c]

[c] Tesla Model S

[2]This definition is admittedly vague and allows for flexibility in the parameter value based on interpretation. This is one of the reasons we explore different model avialability metrics here.

[3]It is possible that the $50k price point would exclude early adopters, who tend to be higher income. As the simulation does not segment the population into early adopters and majority buyers, but rather considers an average consumer choice function, it would be remiss to exclude these models and sales from our study. This is especially true for PHEVs and BEVs which are still clearly in the "early adopter" stage of consumer adoption.

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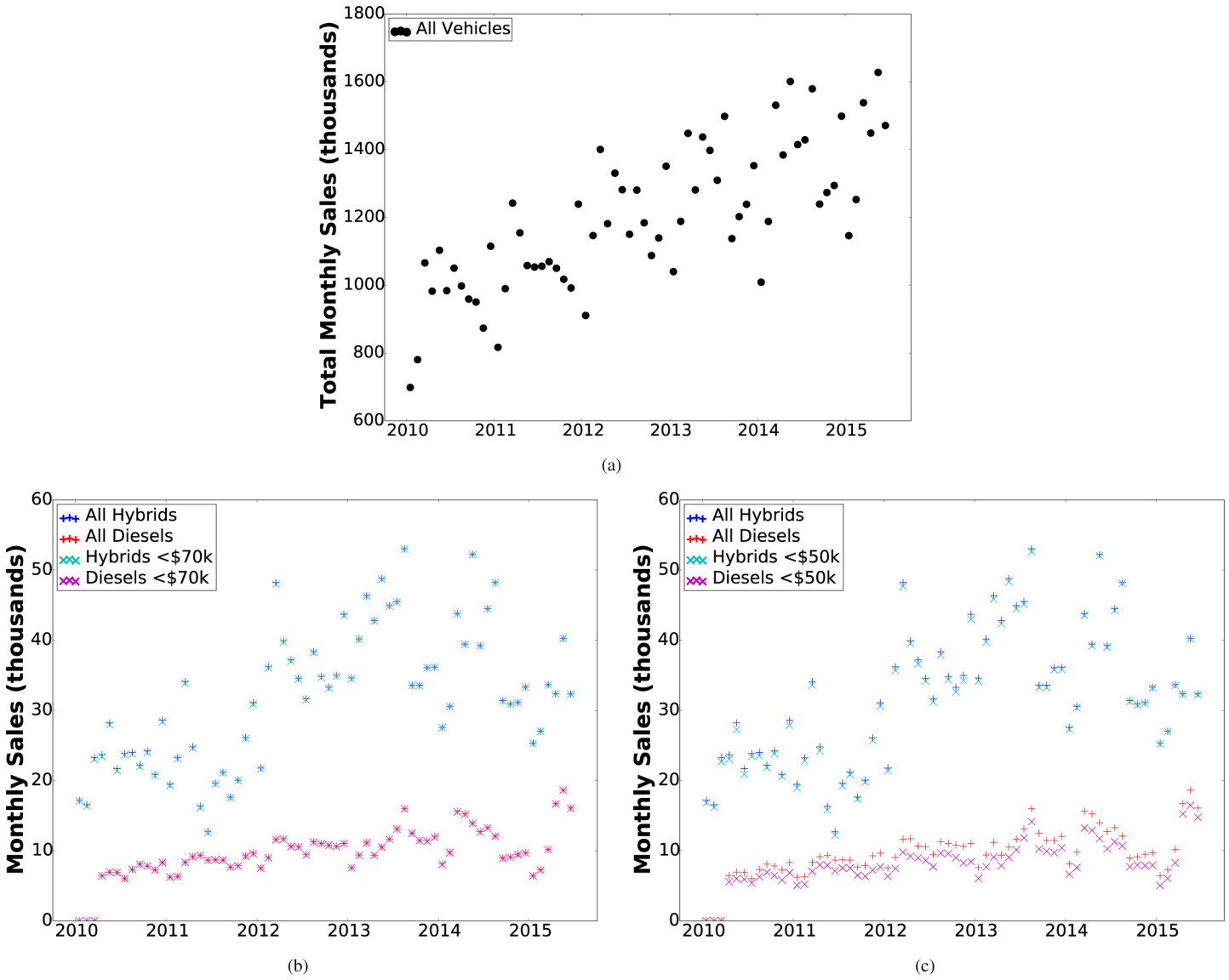

Figure 1. Monthly vehicle sales, and monthly sales of hybrids and diesels from 2010 [18, 19].

We compare simulated to historical sales from *HybridCARS* [18, 19] for diesel vehicles, hybrid vehicles, PHEV10s, PHEV40s, and BEVs with 75mi, 100mi, 150mi, and 225mi ranges. See tables 8 and 9 to see how we categorize existing models into these electric range classes.

Since Tesla is the only manufacturer that has sold electric vehicles in the US in the 150 and 225mi range categories, we don't report on these powertrains explicitly, though we do comment on BEV sales in aggregate across the vehicle ranges. We additionally do not include natural gas vehicles in our study since only one model of non-specialty light duty natural gas vehicle has been available in the US since 2010, and sales fractions for these vehicles are still too small for a meaningful comparison. Last, while the simulation also includes flex fuel vehicles, we could find no corresponding sales data that distinguishes flex fuel vehicles from conventional internal combustion vehicles. Therefore, while sales of these vehicles contribute to total vehicle sales counts in both the actual sales data and the model, we do not compare actual and simulated sales of flex fuel vehicles in this analysis.

DIESEL VEHICLES

Figure 3 shows that between 2010 and 2013, the historical sales fraction of diesel vehicles in the US followed a mostly unremarkable, slow upwards trajectory. Beginning in 2013, diesel vehicle sales begin to fluctuate more, experiencing a sharp rise in mid 2013, and a dip in sales beginning in 2014 and continuing through the first quarter of 2015.

Using the baseline assumption of an S-curve growth in model availability for AEVs, the simulation captures the slow linear growth of diesel vehicle sales through 2013. This projection is shown in figure 3a. The simulation also projects a dip in sales starting in 2014, in line with the sales decrease observed in the historical data. This sales dip is very likely influenced by the decrease in oil price in 2014, and its presence in the simulation, in conjunction with the accurate projections for overall sales growth between 2010 and 2015, indicates that the underlying simulation logic pertaining to changes in consumer choice (e.g. consumer response to changes in oil prices) accurately reflects reality.

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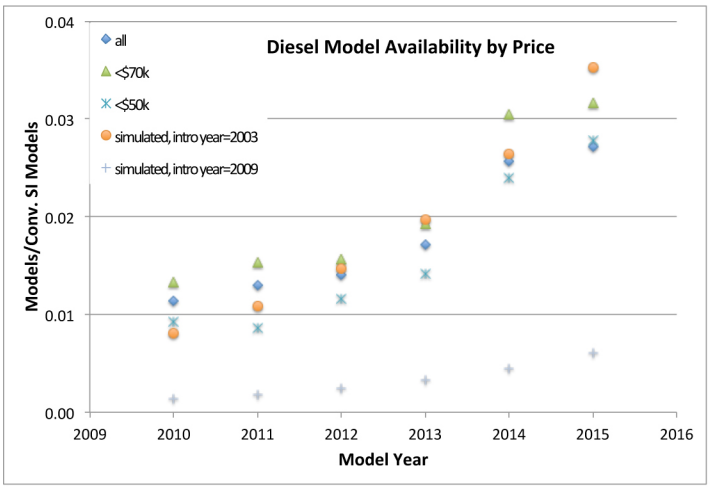
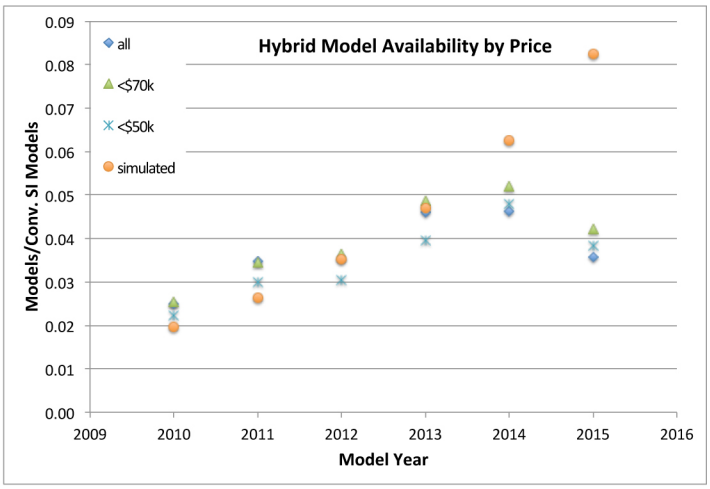


(a)



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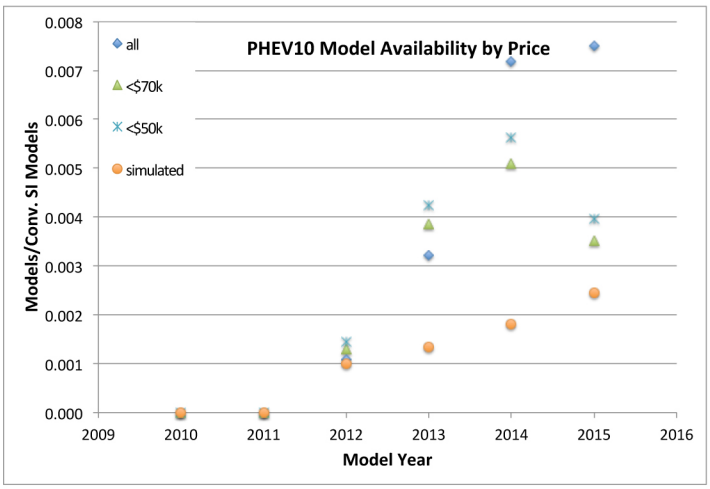

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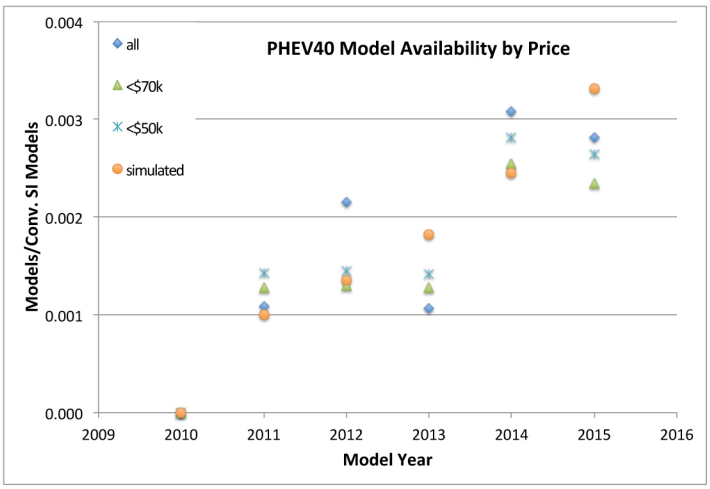

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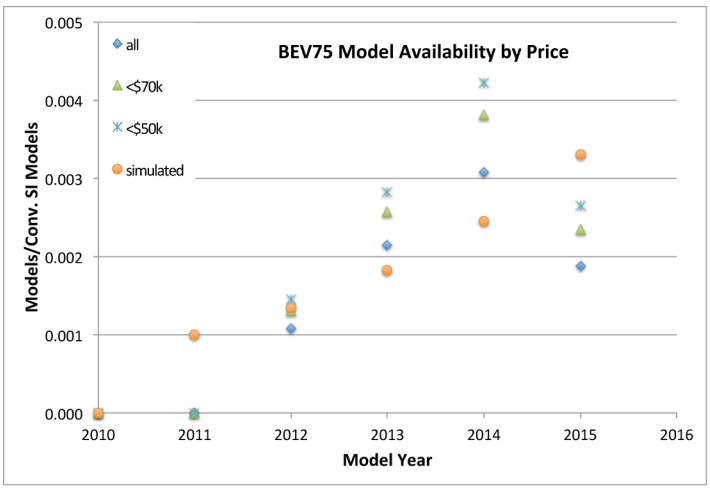

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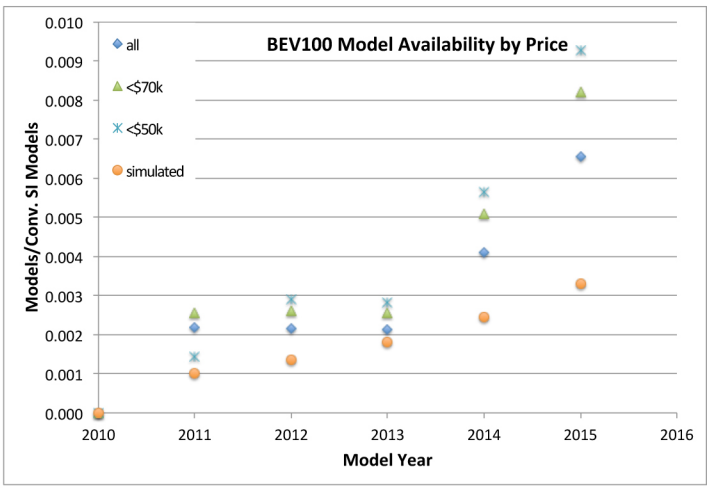

(f)

Figure 2. Relative model availability by year for AEVs. See the appendix for a full list of AEV models and model years.

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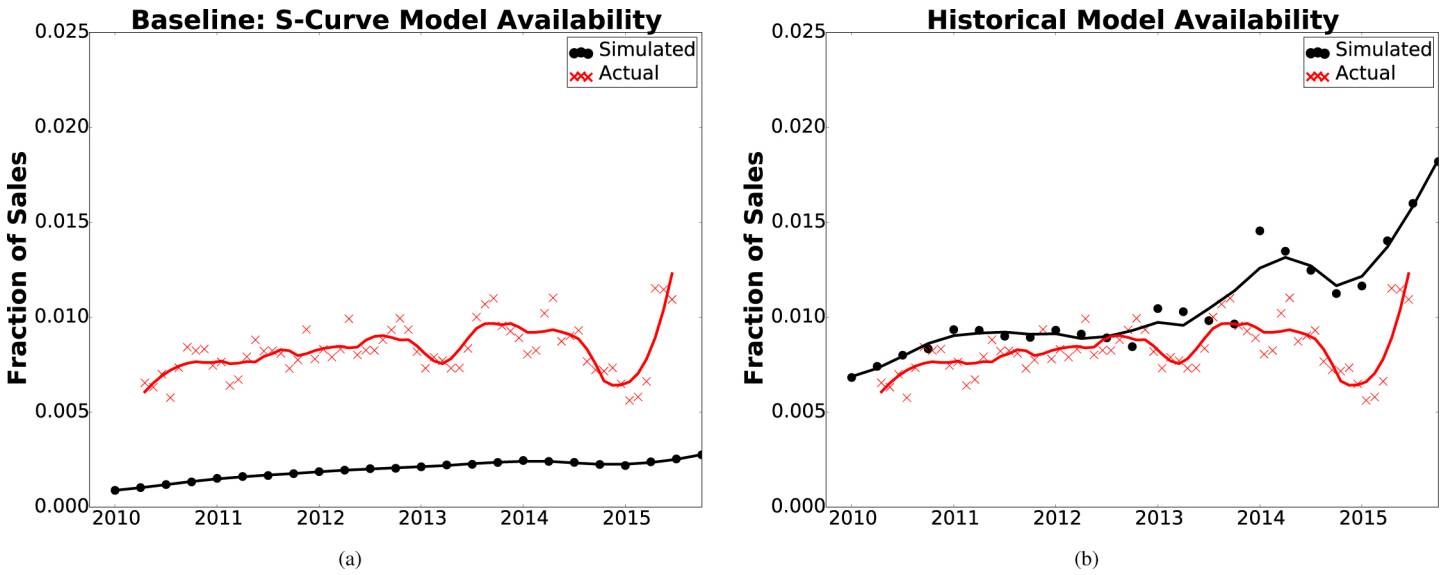

Figure 3. Diesel vehicle historical and simulated sales. Trend lines show Savitzky-Golay smoothed data.

However, the historical vehicle sales are systematically underestimated in this first simulation, indicating that the baseline assumptions are falling short in other respects. And, even though the simulation captures the decrease in sales in 2014, it does not accurately capture the magnitude of the drop in diesel sales observed.

Moreover, this first simulation does not capture the sales fluctuations in 2013 at all. Cobb [37, 38, 39, 40] attributes the lackluster growth of diesel sales in the winter of 2013 to the stagnation of model availability during that period. Correspondingly, the sharp increase in diesel sales in June and July coincide with the release of the diesel versions of the Chevrolet Cruz and the Audi A6, A7, and Q5.[4]

Figure 3b shows the projections when historical model availability is used in lieu of the default assumed S-Curve model growth. The actual model availability of diesels is much higher than the availability computed with an S-curve assuming a 2009 market introduction year. In fact, the model availability more closely reflects an S-curve that assumes a 2003 model introduction year (see figure 2). While the current adoption of diesel vehicles in the US only really began in 2009, the same cannot be said for Europe. In 1990, diesel vehicles comprised nearly 15% of European sales and more than 10% of the light duty stock [41]. By 2010, when diesel sales were still shy of 1% of US LDV sales, they comprised more than half of European sales and 35% of the European stock. The model availability of diesel vehicles in the US was influenced significantly by the mature market of diesel vehicles in Europe. Therefore it is unsurprising that the model availability of diesels in the US is much larger than is indicated by an S-Curve based on a market introduction year of 2009.

Using the historical model availability for diesel vehicles, the simulated sales are much higher, more closely resembling actual sales. Additionally, the simulation accurately reproduces the magnitude of the drop in projected diesel sales in 2014. The simulation also captures the sales jump in 2013, albeit six months delayed. The delay in the sales jump in the model is due to our assumption that models become available for sale in their model year. Therefore, even though the model 2014 Chevrolet Cruze, Audi A6, A7, and Q5, and others entered the market in the summer of 2013, causing a significant sales increase at that time, this model introduction is delayed to 2014 in the simulation and the resulting sales increase follows suit.

We take away the following key points from the comparison of simulated diesel vehicle sales to historical values.

- The simulation logic is sound. The simulation captures the key elements of consumer choice, reflecting consumer response to oil prices and model availability changes, as well as the other underlying drivers (e.g. relative technology prices) that determine AEV sales fractions.
- Consumer choice is very sensitive to model availability. This indicates that increasing model availability might be a powerful way to influence vehicle sales.
- Model availability for diesels in the US closely matches a S-Curve growth pattern for a market introduction year of 2003, not 2009. We have since calibrated the simulation to use this earlier introduction year to predict future model availability of diesel vehicles.

HYBRID VEHICLES

We consider four variations when comparing simulated hybrid sales to actual sales data: the baseline case of S-Curve model availability, the case where historical model availability is used, and two cases for using only non-luxury model availability and comparing to sales data for only non-luxury vehicles.

[4]We note that the fluctuation in 2013 may simply be the result of seasonal buying trends.

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