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Driving the Future: A Management Flight Simulator of the US Automobile Market

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Abstract

Background. A significant gap exists in the United States between ambitious regulatory goals requiring firms to introduce hybrid and electric vehicles, and consumer adoption of these technologies to date. However, the interventions required to close this gap are not obvious due to the complex feedbacks and time delays that govern **alternative fuel vehicle (AFV) diffusion**.

Purpose. The purpose of this article is to introduce *Driving the Future (DtF)*, a free, web-based **management flight simulator** to explore the effects of automaker strategies and public policies on the US automotive market.

Method. We develop a behavioral, dynamic model portraying multiple automobile and fuel types, fueling infrastructure, and consumer choices, enabling users to rapidly experiment with how a wide array of decisions and assumptions shape the dynamics of AFV diffusion out to 2050.

Results. We describe how the simulator can be used to explore various scenarios for AFV adoption, and discuss how the simulator can help improve mental models and decision-making. We present evidence from classroom and online experiments, demonstrating that the simulation is both effective in developing users' understanding of AFV diffusion dynamics, and enjoyable to use.

Keywords

alternative fuel vehicles, management flight simulator, simulation, strategy, policy analysis

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Introduction

Reducing the environmental impacts of automotive transportation is an urgent public health imperative. In the United States, the transportation sector now produces more greenhouse gas (GHG) emissions that any other sector of the economy, including electricity generation and the residential, commercial, and industrial sectors (EIA, 2016a). Light duty vehicles, comprising passenger cars and light trucks, are responsible for 61% of total transportation sector emissions (EPA, 2016). The combustion of oil-based fuels in road transportation is also the leading source of urban air pollution in the United States, responsible for an estimated 53,000 deaths per year (Caiazzo, Ashok, Waitz, Yim, & Barrett, 2013). Automobile demand is growing rapidly in emerging economies including China and India, with the global fleet expected to grow from 1.25 billion vehicles today (Wards Auto 2016) to 2 billion vehicles by 2035 (Navigant, 2014; Sperling & Gordon, 2009). Meeting global sustainability goals, including limiting the worst effects of climate change, will not be possible without a rapid transition to zero-carbon automotive fuels over the coming decades.

A range of technologies have the potential to improve the efficiency of fuel use, such as light-weighting, and to reduce the carbon intensity of automotive fuels, such as electric vehicles and hydrogen fuel cell vehicles—if the electricity or hydrogen can be produced by low-carbon renewables such as wind and solar. Other emerging technologies promise greater transportation sustainability by changing how consumers own and operate automobiles. For example, car-sharing schemes such as Zipcar, and ride-hailing services such as Uber and Lyft, provide the use of automobiles on-demand without the need for personal vehicle ownership. And at the city level, transit-oriented development and multi-model transportation planning seek to reduce automobile dependence.

In the United States, the primary focus of regulators has been on improving the vehicle powertrain, driven by aggressive policies requiring the deployment of these efficient and alternative-fuel vehicles (AFVs). At the federal level, the Corporate Average Fuel Economy (CAFE) mandate requires automakers to improve the average fuel economy of their new vehicle sales to 54.5 miles per gallon (mpg) (4.3 L/100 km)[1] in 'unadjusted' mpg by 2025, equivalent to approximately 41 miles per gallon (5.7 L/100 km) in adjusted or real world terms[2] (NHTSA, 2012). Multiplier credits are provided to firms that sell plug-in hybrid vehicles (PHEVs), battery-electric vehicles (BEVs) and hydrogen fuel cell vehicles (HFCVs). In addition, the Zero Emissions Vehicle (ZEV) mandate adopted by California and several other states supersedes CAFE, requiring automakers to sell an increasing number of zero-emissions electric and hydrogen vehicles, rising to approximately 15% of new vehicle sales by 2025 (CARB, 2016). These high-level policies are supported by technology-specific incentives in numerous government jurisdictions, including income tax credits, sales tax exemptions, and permission to drive single occupant AFVs in high-occupancy vehicle (HOV) lanes, which have had mixed success in accelerating AFV adoption (Diamond, 2009; Gallagher & Muehlegger, 2011).

Table 1. Description of Vehicle Platform Acronyms.

Acronym	Description
BEV	An electric drive vehicle that is propelled by an electric motor, with a large battery to store electricity that can only be recharged by plugging the vehicle in.
BIO	An internal combustion engine vehicle, similar to a conventional gasoline vehicle, that has been modified to run on ethanol biofuel.
DIESEL	An internal combustion engine vehicle, similar to a conventional gasoline vehicle, that has been modified to run on diesel.
GAS	A conventional internal combustion engine vehicle that runs on gasoline.
HEV	A hybrid electric vehicle that combines a conventional gasoline internal combustion engine with an electric motor powered by electricity recovered through regenerative braking to improve the efficiency of gasoline use.
HFCV	A vehicle that is similar to a BEV in that it is propelled by an electric motor, except that the vehicle is refueled with compressed hydrogen, which is converted electricity on board the vehicle by a hydrogen fuel cell.
NGV	An internal combustion engine vehicle, similar to a conventional gasoline vehicle, that has been modified to run on compressed natural gas.
PHEV	A plug-in hybrid vehicle, similar to an HEV, except that it has a larger battery that provides a limited range of fully electric driving, and which can be plugged in to recharge the battery.

However, a substantial gap exists between the ambitious goals of regulators and the current trajectory of the US automotive market. Sales of electric-drive vehicles have failed to take off despite considerable policy support, with PHEVs, BEVs, and HFCVs (see Table 1 for description of acronyms) accounting for little more than 1% of new vehicle sales (Figure 1). Sales of HEVs, including the iconic Toyota Prius, have fared little better: after strong initial growth, sales slowed around 2010, and fell noticeably in the last two years with the pronounced drop in the price of gasoline (Figure 1). Cheap gas has also stalled improvement in the fleet-average fuel economy of US new vehicle sales, with fuel economy plateauing since 2014 as buyers shifted to larger, less fuel-efficient vehicles (Figure 2).

To develop effective policy and strategy measures that close the fleet performance gap, decision-makers must understand the feedbacks that govern the diffusion of emerging AFV technologies. Multiple feedbacks, time delays, and nonlinearities make this task challenging, including: (i) slow turnover of the vehicle fleet; (ii) consumer learning and acceptance of AFVs resulting from marketing and social exposure; (iii) the co-evolution of compatible refueling infrastructure with AFV adoption; and (iv) improvements in key technologies resulting from R&D, learning-by-doing, and economies of scale and scope. These feedbacks create so-called "chicken and egg" dynamics: consumers avoid alternative fuel vehicles unless they are affordable, capable, and offer ubiquitous fuel/charging points, but energy suppliers are reluctant to invest in fueling/charging infrastructure until they are sure there will be a viable market, and the costs and capabilities of the vehicles improve slowly because low AFV sales limit the

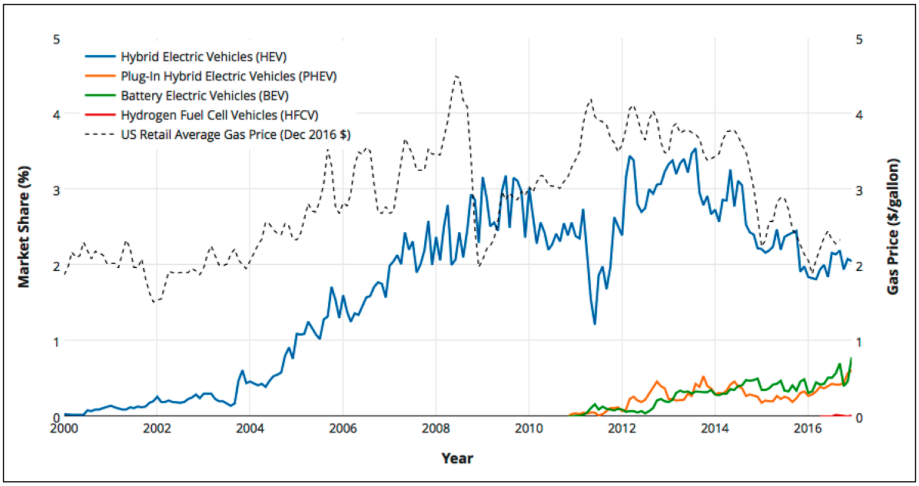

Figure 1. US Monthly Sales of Alternative Fuel Vehicles
(1 gallon ≈ 3.8 litres. Therefore $2/gallon ≈ $0.53/litre, $4/gallon ≈ $1.05/litre).
Data Sources: HybridCars.com (2016), EIA (2016b)

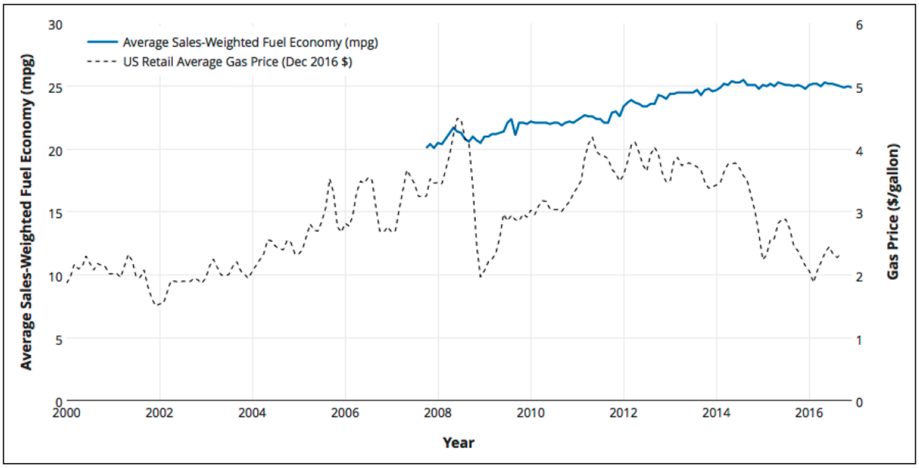

Figure 2. Sales-Weighted Fuel Economy (Window Sticker) of New Vehicle Sales
(20 mpg ≈11.8 L/100 km, 25 mpg ≈ 9.4 L/100 km).
Data Sources: UMTRI (2016), EIA (2016b)

revenue, experience, and scale that could lead to improvement. These dynamics are further complicated by substantial uncertainty in factors that influence the attractiveness of AFVs, including: consumer preferences for vehicle features; the future price of gasoline; regulations mandating AFV deployment (as in California) or the CAFE regulations; and the rate at which key technologies, such as the storage capacity and costs of lithium-ion batteries now used in electric-drive vehicles, can improve.

Computer-based models therefore play an important role in supporting decision-making about automotive technology diffusion, and many such models exist for the United States. For example, the ‘CAFE Compliance and Effects Modeling System’ developed at the Volpe National Transportation Systems Center (commonly referred to as the ‘Volpe Model’) is used to calculate the costs and benefits of CAFE regulations for consumers, manufacturers, and the environment (Volpe, 2017), supported by the ‘Greenhouse Gases, Regulated Emissions, and Energy use in Transportation Model’ (GREET) developed by the Argonne National Laboratory, which calculates full life-cycle energy and emissions impacts of numerous fuel and vehicle technology combinations (ANL, 2015). However, these spreadsheet models are opaque and focus on market segments, powertrain technologies, and fuel pathways in fine detail. Substantial time and effort is required to understand and interrogate these models, and alternative scenarios cannot be readily compared, impeding the development of effective mental models about the interaction of feedbacks including fleet turnover, technological change, consumer learning, and infrastructure coevolution. The Market Acceptance of Advanced Automotive Technologies (MA^3T) model developed at the Oak Ridge National Laboratory for the DOE Vehicle Technologies Program makes significant advances in this regard, articulating an explicit causal structure that includes behavioral factors such as consumers’ loss aversion and access to charging infrastructure, demonstrating the behavior of several pre-specified scenarios through the web-based MA^3T MiniTool interface (ORNL, 2017). Even so, the MA^3T interface does not support the type of interactive experimentation and rapid feedback that is essential if users are to develop their own learnings and improved mental models (Sterman, 2014a).

The consequences of inadequate model support are that industry stakeholders must rely on their intuition to inform decision-making, a method prone to errors in understanding dynamics including accumulation, time delays, and nonlinearities (Sterman, 1994). The history of efforts to promote AFVs in the US is characterized by “sizzle and fizzle”, in which repeated efforts to introduce technologies ranging from hydrogen and biofuels to electric vehicles have collapsed when the initial burst of enthusiasm and investment fails to deliver tangible progress (Stewart, 2010). Short-lived incentive programs (Berman, 2011, Dillon & Megerian, 2016), unrealistic deployment targets (Tuttle, 2015), and inconsistent firm technology strategies (Griemel, 2014) suggest that industry stakeholders lack a shared understanding of the extent, timing, and coordination of decisions that are necessary to create markets for AFVs that are sustainable not only ecologically but also economically.

In this article we introduce *Driving the Future* (*DtF*), a management flight simulator that supports improved policy and strategy decision-making about the diffusion of AFV technologies in the United States. The *DtF* model is technology-neutral, and the simulator does not favor a specific market outcome. *DtF* enables users to implement a variety of policy and strategy measures for analysis of the market from the perspective of multiple different stakeholders. *DtF* is accessed through a freely available web interface (http://bit.ly/DtFsim) that can be easily understood without prior knowledge by a wide range of stakeholders, from automaker executives and policymakers to the general public. Because future technology pathways in the US automotive market are

Table 2. Vehicle Platforms and Fuel Compatibility.

Fuel Platform	Gasoline	Electricity	Diesel	Compressed Natural Gas	Ethanol (E85)	Hydrogen
GAS	✓					
HEV	✓					
PHEV	✓	✓				
BEV		✓				
DIESEL			✓			
NGV				✓		
BIO					✓	
HFCV						✓

inherently uncertain, the goal of the simulator is not to generate predictions about the future, but to help users develop insights about how the market may respond to policy and strategy measures. Opportunities for learning therefore exist in the comparison of scenarios that implement differing suites of policy and strategy measures.

Model

DtF is a feedback-rich behavioral model that simulates the composition of the US light-duty vehicle fleet over time and the energy and environmental impacts that result. *DtF* is parameterized for the fleet size, vehicle technology mix, fuel pathways, and policy landscape in the US today. The model represents eight vehicle platforms and six compatible fuels (Table 2).

The fleet of vehicles of each platform on the road accumulates new vehicle sales less vehicle retirements that occur due to old age and crashes. The market share of each vehicle platform in the model is contingent on: (i) the utility of that platform, and (ii) the willingness of consumers to consider that vehicle platform in their purchase decision. Consumers will only consider purchasing a platform when they are sufficiently familiar with it that they are willing to include it in their consideration set (Hauser & Wernerfelt, 1990). Achieving this consideration requires consumers to learn about the platform through social interactions such as seeing commercials on television, discussions with friends who have purchased it previously, and observing the vehicles in use. Consumer consideration of each vehicle platform accumulates with social exposure to that technology from advertising and word-of-mouth. The utility of each vehicle platform depends on its attributes (including purchase price, operating cost, greenhouse gas emissions, and refueling convenience), which evolve through feedbacks including the coevolution of refueling infrastructure with fuel demand, and learning-by-doing and R&D investment by producers that lead to cost reductions.

The *DtF* model has various simplifications and limitations, as all models do. For example, the model does not distinguish among vehicle body styles, concentrating on consumer choices between competing powertrain technology platforms; a single representative variant of each technology platform is available to consumers; the used vehicle market is not represented; and the model does not disaggregate regional markets within the United States. More broadly, the model represents the existing market structure in the United States currently dominated by privately owned vehicles, and does not yet capture emerging technologies such as car sharing, mobility services, and hybrid forms of public-private transportation that are being developed in different markets around the world. *DtF* is therefore complementary to more detailed models, providing important dynamic insights to users who are mindful of these limitations, and has been used successfully to facilitate discussions with stakeholder groups including automotive industry executives, students, and the general public.

We introduce the core structure of the model below, describing our modeling approach and then elaborating on the formulations and behavior of key sub-models. We first describe the fleet model that tracks the composition of the on-road vehicle fleet over time. Second, we describe the consumer choice structure used to estimate the market share of new vehicle sales achieved by each vehicle platform. We then elaborate on the three main feedbacks in the model: the accumulation of consumer consideration; the co-evolution of refueling infrastructure; and endogenous technological change. Full documentation of the model is available at: http://bit.ly/DtFdocumentation.

Modeling Approach

The *DtF* model is developed using System Dynamics, a modelling approach used for the analysis of complex social, economic, environmental, and human systems. System Dynamics was developed by Prof. Jay Forrester at the Massachusetts Institute of Technology in the 1950s, who recognized that the principles of feedback control being used in engineering could also be used in the management of large-scale real-world systems, from the performance of organizations (Forrester, 1961), to cities (Forrester, 1969) and environmental sustainability (Meadows, 1972, Meadows, Randers, & Meadows, 2004).

Central to System Dynamics is the concept of feedback: the behavior of a system is viewed as an endogenous consequence of the interactions that occur between the elements in that system. Feedback loops exist when the consequences of an action travel through a system and return, potentially changing the state of the system and influencing future behavior (Richardson, 1991). Two types of feedback loops exist. Loops are labeled ‘reinforcing’ when the consequences of an action lead to more of that action occurring subsequently. For example, the accumulation of interest earned on a bank balance increases the bank balance, which will lead to even more interest being earned in future (without withdrawals). Loops are labeled ‘balancing’ when the effect of an action is to counteract the initial action. For example, if a room gets cold, the thermostat turns on the heating system, which will be heating the room until the temperature of the room becomes equal to the number on the dial of the thermostat, which then turns off the heat. Alternatively, if in any simple market the demand is higher than the supply, it would increase the prices, which would force some potential buyers to drop out and decrease the demand, thus returning the system to the equilibrium where

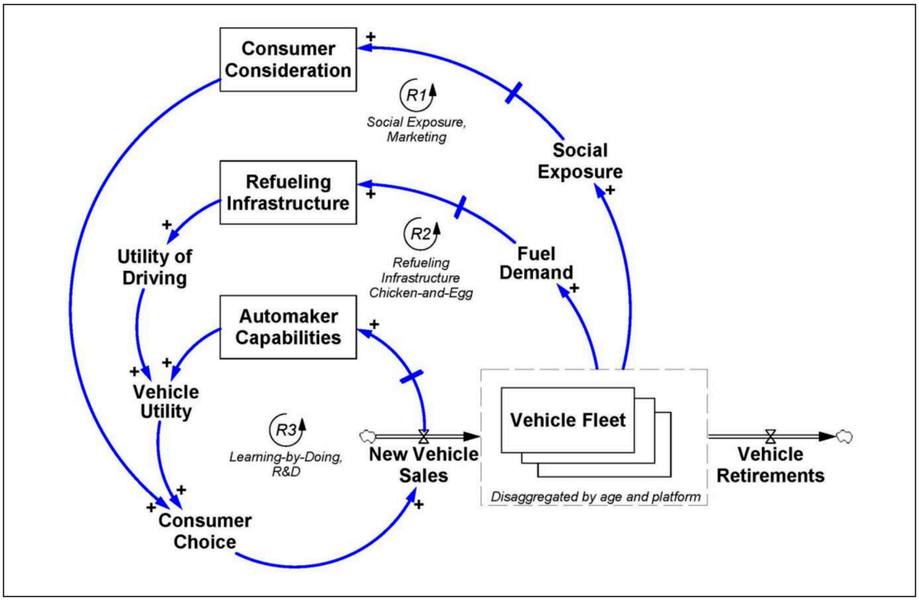

Figure 3. Model Overview.

demand is equal to supply. All balancing loops are working towards bringing the system to an explicit goal. For example, a hot cup of tea left sitting on a table will cool at a progressively slower rate until it is the same temperature as the ambient temperature in the room. The other key building blocks of System Dynamics models are stocks and flows. Stocks are accumulations of flows that indicate the state of the system and which are the basis for future action. For example, the amount of money in a bank account is a stock, which influences the amount of interest that is earned on that account. Stocks decouple trajectories of flows. For example, if a net flow to a stock becomes zero or even negative, the stock doesn't disappear immediately, as it takes time to drain it, similar to a bathtub.

Using these elements, the causal structure of a system can be articulated in a Causal Loop Diagram such as Figure 3, which shows the high-level structure of the *DtF* model. Stock variables are indicated with boxes, while flows are visualized as a pipe governed by a valve. Variables are linked by causal arrows, each labelled with a polarity indicating the nature of the causal relationship. A '+' indicates that, *ceteris paribus*, an increase (decrease) in the causal variable leads to an increase (decrease) in the dependent variable. A '–' indicates that, *ceteris paribus*, an increase (decrease) in the causal variable leads to a decrease (increase) in the dependent variable (Sterman, 2000). Hash marks on a causal arrow indicate a delayed effect. For example, refueling infrastructure lags fuel demand due to the time required for fueling infrastructure providers to determine that changes in fueling capacity are needed, and then to select locations, acquire permits, and build the capacity. Feedback loops are then labelled with an 'R' to denote a reinforcing loop, or a 'B' to denote a balancing loop, based on the net effect of the causal influences that comprise that feedback loop. Figure 3 highlights three key reinforcing loops that govern AFV diffusion. For example, in the infrastructure coevolution feedback, if more BEVs are sold, the number of BEVs on the road increases, increasing demand for recharging, leading the construction of more charging stations, making driving a BEV more attractive, leading to yet more sales. If operating virtuously, as described here, these reinforcing loops should result in exponential growth in BEV adoption. However, these same reinforcing feedbacks can operate as vicious cycles: with few BEVs on US roads, demand for charging stations is low, so few new stations are built, meaning that recharging a BEV remains difficult, and so few new BEVs are sold. This example highlights the challenge of successful AFV introduction: new technologies that are initially expensive, unfamiliar, and require their own specialized refueling infrastructure are competing against a deeply established incumbent (gasoline) that is affordable, accepted by consumers, and offers ubiquitous refueling stations.

To simulate the dynamics resulting from these feedbacks, the model is formalized as a system of coupled, non-linear, ordinary differential equations. The model is based on established formulations and grounded in empirical studies. For example, we use the standard nested multinomial logit formulation in our representation of consumer choice (Train, 2009), and power-law learning curves in our representation of endogenous technological change (Argote and Epple 1990).

Vehicle Fleet

The model is parameterized for the US light duty vehicle market, assuming a constant total vehicle fleet size of 240 million vehicles, and an average vehicle life of 15 years, resulting in 16 million new vehicle sales/year.[3] We represent the vehicle fleet with a standard vintaging structure (Sterman, 2000), with 4 cohorts, and cohort-specific hazard rates of retirement that increase with vehicle age (Greenspan & Cohen, 1999). The vehicle fleet in 2000 was comprised almost entirely of gasoline vehicles, with only 100,000 diesel vehicles and no other platforms present. The fleet composition then changes over time in response to the mix of new vehicles sold and on-road vehicles retired due to crashes and aging.

The model tracks the greenhouse gas (GHG) emissions of each vehicle platform on a per-mile basis in metric tons of CO_2-equivalent, which are then aggregated to calculate annual GHG emissions by vehicle platform, by fuel, and for the entire fleet, based on vehicle fleet composition and platform vehicle-miles travelled. GHG emissions are calculated using well-to-wheels emissions factors from GREET (2016), which include both tailpipe emissions during vehicle operation and emissions from upstream fuel production. The model includes cost and emissions assumptions for multiple upstream fuel pathways, including conventional and renewable pathways for electricity and hydrogen. The model also allows for the GHG emissions from the US electrical grid vary endogenously as the mix of renewable and fossil generation sources responds to the costs of renewable versus fossil inputs to electricity production.

Consumer Choice

New vehicle buyers in the United States have a choice from a wide range of makes, models, body styles, and powertrain technologies. The choice of powertrain technology - internal combustion powered by gasoline or diesel, hybrid electric, full electric, biofuel, hydrogen fuel cell, etc., hereafter referred to as the 'vehicle platform' - strongly conditions energy consumption and environmental impacts. The model therefore focuses on consumer choices among the various platforms, and does not represent individual makes or models.

Drivers who need to replace their vehicle choose whether to buy another of the same platform or switch to another platform. For example, drivers of conventional gasoline powered vehicles may choose to buy another such vehicle or switch to a battery-electric vehicle. Formally, we estimate the fraction of drivers currently driving platform i who buy platform j, σ_{ij}, using the nested multinomial logit (NMNL) structure shown in Figure 4 (Train, 2009).

We estimate the utility of platform j, u_{ij}, as a linear function of the attributes a of the platform j, χ_{ja}, and consumers' willingness-to-consider that platform, C_{ij}:

$$u_{ij} = \sum_{a} \beta_a \chi_{ja} + \ln\left(C_{ij}\right) \tag{1}$$

where β_a is vector of parameters reflecting the relative weights that consumers place on the attributes of vehicle platform j.

For the purpose of simulating consumer choice, we adopt coefficients for the attributes of the vehicle as estimated by Brownstone, Bunch and Train (2000). In addition, we include the costs to drivers of searching for fuel and refueling: the longer drivers spend finding a fuel/charge point and refueling/recharging their vehicle, the lower the utility of the vehicle will be—having to go out of one's way to find a charge point for a BEV and waiting hours to recharge the battery lowers the utility of BEVs compared to gasoline vehicles, which can be refueled in minutes at multiple, convenient locations. We also add the effect of platform scope, assuming that there will be a wider range of makes and models available to consumer as that platform grows, increasing platform utility. These parameters, drawn from existing studies, are shown in Table 3:

Consumer Consideration

Willingness-to-consider C_{ij} captures the extent to which drivers of platform i are sufficiently familiar with platform j that they include that alternative in their consideration set, the subset of alternatives that they evaluate in detail to purchase (Hauser and Wernerfelt 1990). We model consideration as a stock that represents the "…cognitive and emotional process through which drivers gain enough information about, understanding of, and emotional attachment to a platform for it to enter their consideration set" (Struben & Sterman, 2008). The fractional willingness of consumers currently driving platform i to consider purchasing platform j increases with social exposure to platform j, and erodes as the salience and relevance of older experience and exposure to the platform fade:

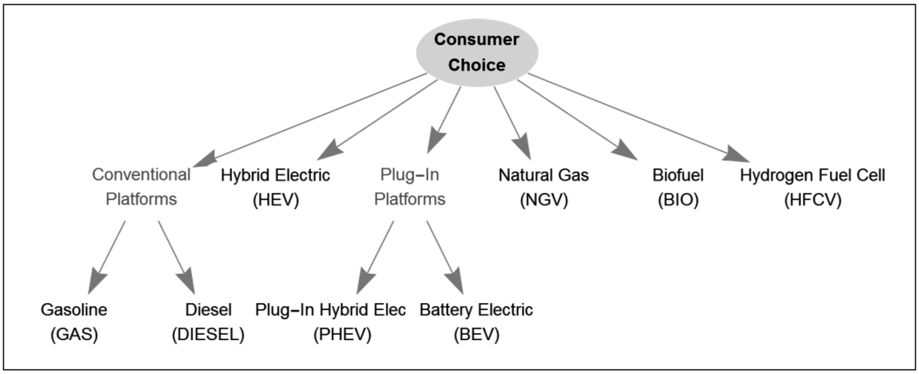

Figure 4. Nested Logit Consumer Choice Structure.

Table 3. Utility Function Coefficients.

Coefficient	Units	Value	Reference
Purchase Price	1,000$/ln(1,000$)	–0.361	Brownstone, Bunch and Train (2000)
Operating Cost	cents/mile	–0.170	
Acceleration	0-30mph (seconds)	–0.149	
Top Speed	100*miles/hour	0.641	
Range	100*miles	1.268	
Range squared	$(100\text{*miles})^2$	–0.116	
Emissions	dimensionless index	–0.673	
Fuel Search Cost	cents/mile	–0.170	Equal to Operating Cost
Platform Scope	dimensionless	0.500	Assumption

$$\frac{dC_{ij}}{dt} = z_j\left(1 - C_{ij}\right) - \phi C_{ij} \tag{2}$$

where z_j is the rate at which consumers receive social exposure to platform j and ϕ is the fractional rate of forgetting. Total social exposure, z_j, is the sum of the effect of marketing about platform j, z_j^m, and the effect of word-of-mouth arising from drivers of platform j, z_j^d. Word-of-mouth is an important reinforcing feedback that contributes to consumer acceptance of new technologies: as the installed base of platform j grows, more opportunities are created for potential buyers to learn about the platform from previous buyers, resulting in greater adoption of the platform.

Consideration is critical in determining the share of each platform: If consumers driving platform i have no awareness of platform j then the market share of platform j among those consumers, σ_{ij}, is zero regardless of the objective utility of that platform, because those drivers simply don't know about and therefore cannot consider purchasing platform j. Driver consideration of a new platform is zero prior to its introduction to the market as consumers necessarily have no experience with or social exposure to platforms that do not exist; consideration must build over time through marketing and other means (such marketing could begin prior to commercial introduction).[4]

Refueling Infrastructure Co-Evolution

The availability of refueling infrastructure is a critical enabler of AFV diffusion. Without easy access to refueling stations, the search for fuel is prohibitively expensive and time-consuming, limiting the effective range of the vehicle through "range anxiety" as consumers seek to "top off" to avoid unplanned out-of-fuel situations. The result is the infrastructure-AFV chicken-and-egg problem: drivers are reluctant to buy AFVs unless they believe they can get fuel anytime and anywhere, while infrastructure providers will not build new refueling infrastructure unless they are sure there will be demand for the fuel. Vehicles and refueling stations therefore co-evolve in a reinforcing feedback that can aid the formation of AFV markets, but that can also prevent AFV diffusion when no refueling infrastructure exists.

Available fueling infrastructure increases with the completion of new infrastructure construction and decreases with the retirement of old infrastructure. The rate at which fueling infrastructure construction starts depends on the desired amount of infrastructure for each fuel type f, I_f^d, which is determined by the stock of the existing infrastructure (I_f) and effects of profitability (β_p) and utilization (β_u) of the existing refueling stations (Equation (3)). The construction of new infrastructure is more attractive when existing stations are more profitable, and when their utilization of existing stations is high—both salient signals to fuel providers that new capacity is warranted.

$$I_f^d = I_f \beta_p \beta_u \tag{3}$$

The availability of refueling infrastructure influences the utility of AFV platforms in multiple ways. As the number of refueling stations increases, the opportunity cost of the time spent searching for fueling decreases, the expected wait time prior to refueling decreases, and the risk of running out of fuel prior to refueling decreases, all making compatible AFV platforms more attractive for consumers. The availability of refueling infrastructure also influences the effective range of AFVs, because drivers maintain a fuel buffer, a portion of their vehicle's range that they reserve for the search for fuel. All else equal, greater fuel availability allows drivers to maintain a smaller fuel buffer and refuel less often. The *DtF* model assumes that drivers maintain a buffer that minimizes their total cost of refueling.

Automaker Capabilities and Technological Change

Currently available AFVs are inferior to conventional gasoline vehicles today on the basis of performance relative to price, hampered in part by high costs for key components such as lithium-ion batteries and hydrogen fuel cells, but also in terms of range, passenger and cargo space, and other dimensions. However, new technologies commonly improve over time, as manufacturers achieve improvements through R&D and learning-by-doing (Argote & Epple, 1990; Arrow, 1962). Endogenous technological change is represented in the *DtF* model for: (i) the cost of individual vehicle subsystems, (ii) the fuel economy of internal combustion engines, and (iii) the power (dispensing rate) of electric vehicle recharging stations.

The cost of each vehicle platform j is modeled as the sum of the costs of each subsystem in that vehicle, including the body, powertrain, energy storage, and other platform-specific technologies. Cost reductions in each vehicle subsystem level a are represented using standard power-law learning curves cumulative in: (i) experience from manufacturing (learning-by-doing), and (ii) investment in R&D:

$$C_{j,a} = C_{j,a}^{0}\left(\frac{E_{j,a}}{E_{j,a}^{0}}\right)^{\log_2(1-\beta)}\left(\frac{R_{j,a}}{R_{j,a}^{0}}\right)^{\log_2(1-\beta)} \tag{4}$$

where for platform j and subsystem a, $E_{j,a}$ and $R_{j,a}$ are cumulative experience and R&D investments, respectively, $E_{j,a}^{0}$ and $R_{j,a}^{0}$ are initial experience and R&D investments, respectively, and β is the learning rate. Learning is assumed to spill over across platforms to the extent that vehicles subsystems are common to multiple platforms. For example, vehicle light-weighting through e.g. carbon fiber composite body panels are applicable to all platforms, but improvements in internal combustion engine performance does not spill over to electric or fuel cell vehicles.

The fuel efficiency of each vehicle platform F_j improves over time as a result of two separate mechanisms – learning-by-doing in production, and pressure on automakers to comply with CAFE that affects vehicle design choices and R&D investments:

$$F_j = F_j^{0}\delta_{FE}\delta_{CAFE} \tag{5}$$

where δ_{FE} is the effect of learning on fuel efficiency, δ_{CAFE} is the effect of CAFE policies, and F_j^{0} is a reference (initial) fuel efficiency of platform j at the time of introduction to the market.

First, efficiency improves via a standard power-law learning curve cumulative in R&D spending for fuel efficiency, which is a fixed fraction of total platform revenue:

$$\delta_{FE} = \left(\frac{R_{FE}}{R_{FE}^{0}}\right)^{\log_2(1-\beta_{FE})} \tag{6}$$

where R_{FE} and R_{FE}^{0} are cumulative and initial R&D investments in fuel efficiency respectively, and β_{FE} is the learning rate for fuel efficiency. Second, the effect of CAFE on fuel efficiency increases asymptotically over time, applying maximum pressure in the year 2025 when full CAFE compliance is required:

$$\delta_{CAFE} = \int \frac{\left(\delta_{CAFE}^{MAX} - \delta_{CAFE}\right)}{\tau} dt \tag{7}$$

Finally, the power (dispensing rate) of electric vehicle charging stations is modeled using a power-law learning curve cumulative in battery sales, comprising endogenous battery sales in the United States from the model plus assumed battery sales globally, reflecting the accumulation of automaker experience with electric vehicle power electronics. Full description of the model structure is available in the model documentation (http://bit.ly/DtFdocumentation).

Model Calibration and Testing

The usefulness of the *DtF* model depends on the extent to which the model is robust, replicating the patterns of diffusion that have been observed to date while also generating plausible diffusion trajectories across a wide range of alternative futures. Calibration to historic data on AFV diffusion in the United States is challenging, because the AFV market remains embryonic. AFVs account for no more than 4% of new vehicle sales to date, meaning the dynamics of diffusion are not readily observable and econometric estimation of parameters and comparison of model behavior to historical data are not yet possible. The lack of such data is an inevitable characteristic of any model to be used prospectively for markets and products that do not yet exist or have not yet been adopted; by the time sufficient data are available, the opportunity to shape the pattern of diffusion will have passed. We therefore build confidence in the model through careful calibration and extensive testing. We consulted numerous subject matter experts, including industry executives, policymakers and researchers, and carried out extensive sensitivity tests to ensure that the resulting diffusion dynamics are both internally consistent and robust across a wide range of scenarios and conditions, e.g., a wide range of future gasoline prices, different learning curve strengths for AFV technologies, and various consumer preferences (See Appendix 1 for analysis of the model's sensitivity to key parametric assumptions).

User Interface

The *DtF* interface is web-based and compatible with all major browsers on PCs and tablets, developed in collaboration with Forio (www.forio.com) using the Forio Epicenter platform. Here we describe how the interface allows the user to rapidly explore the dynamics of AFV diffusion under different technology, policy, and strategy scenarios. An instructional video demonstrating the interactive behavior of the simulator is available at: http://bit.ly/DtFdemo.

Policy and Strategy Levers

DtF includes a wide range of policies and strategies automotive industry stakeholders may use to influence the trajectory of AFV diffusion (Table 4). These interventions include policies and strategies that have been implemented in the US automotive market or considered for implementation.

Users can vary both the availability and extent of interventions as the simulation progresses, implementing policies and strategies individually or concurrently. The model reports the total cost of policies and strategies implemented by stakeholder group, aiding assessment of the economic and political viability of the decisions implemented by the user.

User Screens

Scenario assumptions. Before starting a simulation, the user is presented with a screen defining the high-level scenario assumptions (Figure 5). Here users select options including when each vehicle platform is introduced into the market, the strength of the learning curves for vehicle efficiency and for new fuels (bio, hydrogen), and future prices for gasoline, electricity, and natural gas.

After choosing the scenario assumptions, users are taken to the Simulator Dashboard, which provides graphs and data for key variables that show the current state of the market (Figure 6). Upon arriving at the Dashboard the simulation advances to the year 2015 using historical data, at which time the user takes over management of the market through to year 2050.[5] At any time, the user can alter the mix of policies and strategies implemented in the market (shown in Table 4), then advance a chosen number of years. After advancing, the dashboard displays the results, providing the user with immediate feedback on the outcomes of their decisions. Game play continues iteratively until the end of the simulation in 2050. At any time the user can choose to either: (i) Restart the simulation, keeping the existing policy and strategy settings in place, or (ii) Reset all decisions to the default levels. The first approach is useful for users seeking to refine their strategy rapidly through successive trials, while the latter allows users to start a new set of simulations from scratch. In our experience, users develop their understanding of the dynamics and challenges of creating successful AFV markets faster when they carry out many simulations rapidly rather than laboring over the specifics of a single scenario.

The dashboard provides a range of tools that aid the user's exploration of the simulation. First, clicking on any of the graphs on the dashboard provides a larger view of that graph along with more detailed supporting information. For example, clicking on the dashboard's greenhouse gas emissions graph displays graphs of both total fleet greenhouse gas emissions over time, and emissions per mile by vehicle platform over time. Second, clicking on vehicles and fuel types in the dashboard legend toggles these data series on/off in the dashboard graphs so that users can choose which data to highlight. Third, users can save simulation runs and compare them to other runs through the *DtF* interface, or download them in CSV format for further analysis.

Policy and strategy decisions. The lower half of the screen, accessible either by scrolling down or clicking the Policies button at the top of the screen, allows users to choose the mix of policies and strategies currently active in the simulation (Figure 7). Decisions are implemented by moving sliders across a plausible range of policy values. The user

Table 4. Policy and Strategy Interventions.

Policy/Strategy	Effect	Units
Government Incentives		
AFV Tax Incentive (by Vehicle Platform)	Lowers the purchase price of AFV platforms to encourage consumer adoption.	$/vehicle
Refueling Infrastructure Tax Incentive (by Fuel)	Lowers the cost of refueling station construction to encourage faster development of refueling infrastructure by fuel providers.	$/pump or charge point
Refueling Infrastructure Introduction Program (by Fuel)	Construction of refueling stations to make alternative fuels available for AFV drivers.	Pumps or charge points/year
Taxes		
Carbon Tax	Increases the cost of fuels in proportion to their carbon content.	$/ton CO_2e
Gas Tax	Increases the cost of gasoline and diesel fuels.	cents/gallon gasoline-equivalent
Vehicle Miles Travelled (VMT) Tax	Increases the cost of driving in proportion to the number of miles driven.	cents/mile
Automaker Strategies		
AFV Subsidy (by Vehicle Platform)	Lowers the purchase price of AFV platforms to encourage consumer adoption.	$/vehicle
Additional Marketing (by Vehicle Platform)	Increases consumer consideration of AFV platforms to encourage consumer adoption.	$Million/year
Investment in Fuel Economy R&D	Alters the fraction of total automaker R&D spending that is invested in improving vehicle fuel economy.	% of auto industry revenue
Fuel Providers		
Source of Electricity for EV Charging	Mandate the use of renewable electricity for EV charging.	conventional or renewable
Source of Hydrogen for HFCV Refueling	Mandate the use of renewable hydrogen for HFCV refueling.	conventional or renewable

can also override the maximum value of the slider by typing any desired value into the field provided.

Stakeholder summary. The stakeholder summary view accessed from the dashboard provides an overview of indicators showing the outcomes important to key

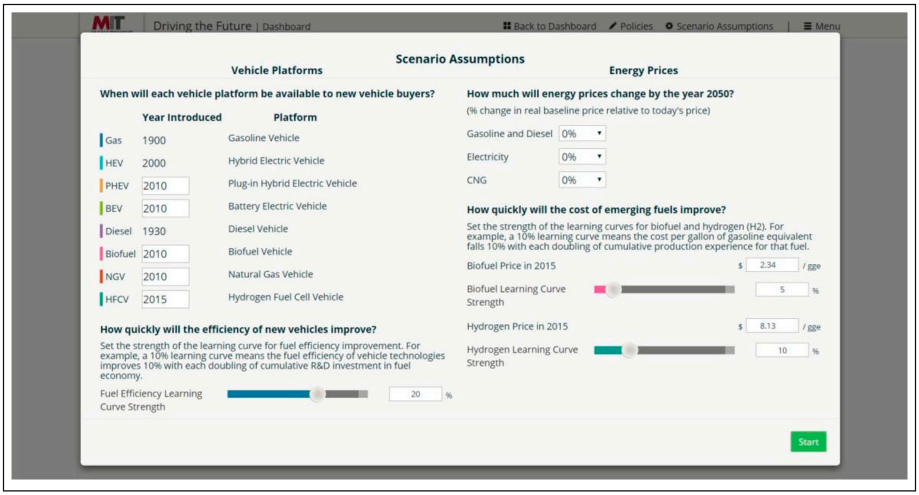

Figure 5. Scenario Assumptions.

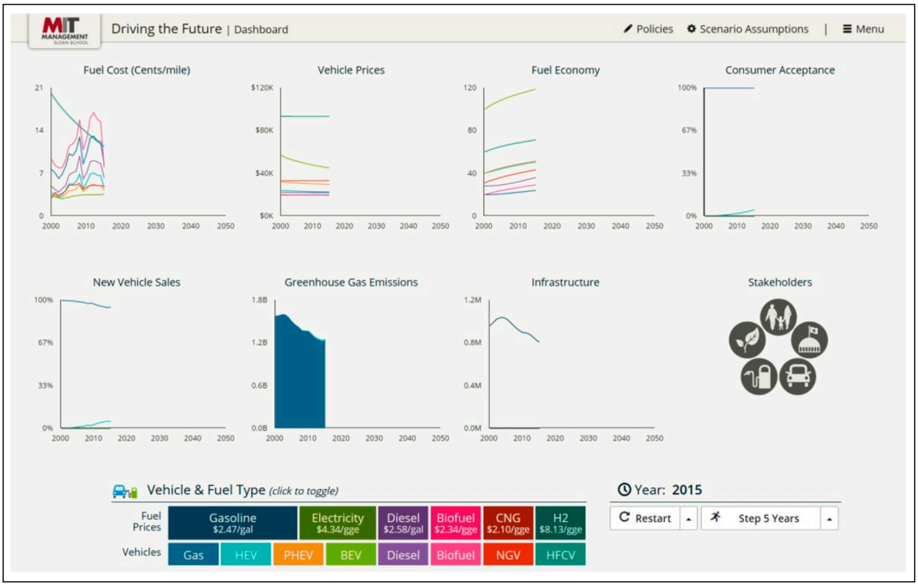

Figure 6. Dashboard.

stakeholders including consumers, the environment, fuel providers, governments, and automakers, allowing users to assess the costs and benefits of their decisions (Figure 8). The stakeholder view also enables the simulator to be used in a multi-player mode where different people play the role of different stakeholders, each focused on the outcomes they care most about.

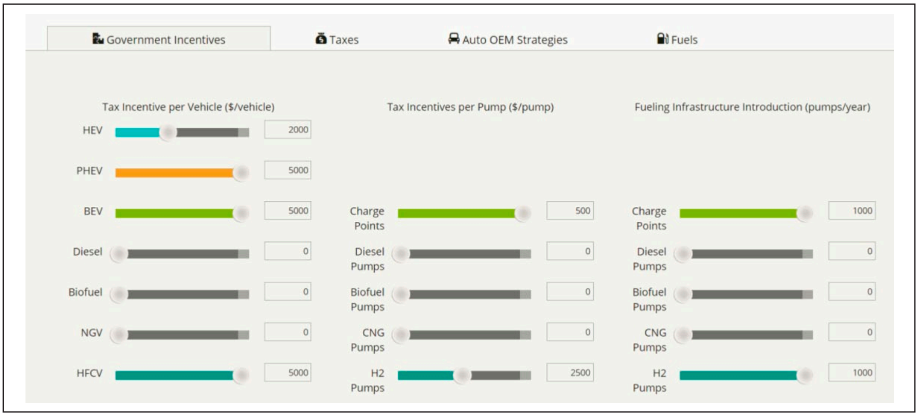

Figure 7. Policy and Strategy Settings.

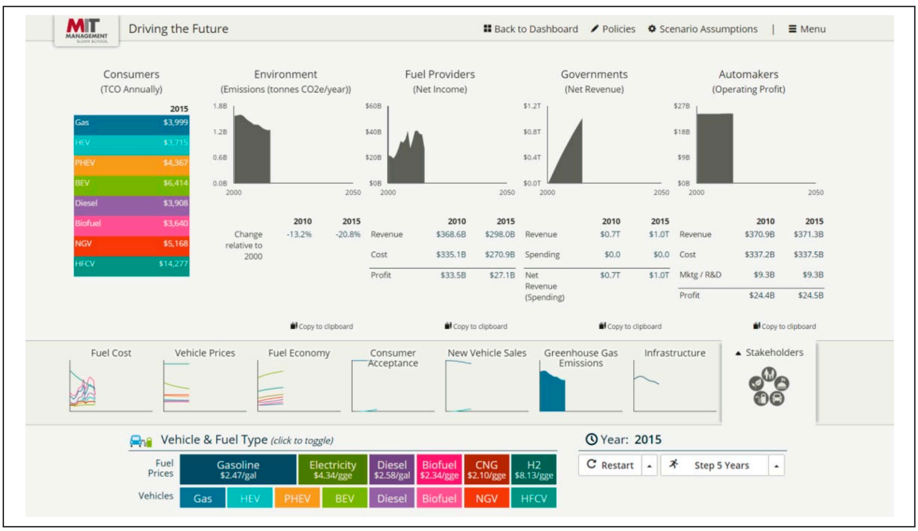

Figure 8. Stakeholder Summary.

Class Facilitation

The simulator includes an administrator interface enabling instructors (teachers or workshop facilitators) to see the simulation results of class participants in real time, sort participants' scenarios according to key variables such as the market shares of AFV platforms, and download the results of all participants for further analysis. Instructors can also set up a "class" consisting of particular settings all participants will use. Instructors choose the assumptions for each scenario, and can set up as many

Figure 9. Baseline Scenario.

as they like to provide a structured learning sequence. For example, the instructor may set up a first scenario in which gasoline prices remain low, another in which they rise, and another in which a carbon price is enacted.

Illustrative Scenarios

Three illustrative scenarios demonstrate the behavior of the *DtF* model: a baseline scenario and two scenarios that implement suites of policies designed to accelerate consumer adoption of electric vehicles.

The baseline scenario uses the default assumptions and default (zero) policy and strategy interventions. The baseline provides a reference to evaluate the impact of policy tests (Figure 9). The baseline scenario is counter-factual, in that it does not include policies that exist in the United States currently, such as federal (and some state) tax incentives for the purchase of plug-in electric vehicles. In the baseline, sales of conventional hybrid vehicles (HEV) grow steadily as consumers become increasingly willing to consider HEVs in their purchase decision, and as HEVs become cheaper and available in a wider range of makes and models as a result of learning-by-doing and R&D. In contrast, sales of all other AFV platforms remain negligible. Because vehicle costs for those platforms remain high, few are willing to buy; without an emerging market to generate social exposure, consumers are reluctant to include these vehicles in their consideration set. Further, without demand for electric vehicle charging or other alternative fuels, investment in refueling infrastructure remains low, limiting fuel availability and suppressing purchases even among the few consumers willing to consider AFVs. Importantly, the fuel economy of conventional and hybrid (gasoline powered) vehicles increases through learning and R&D. The resulting increase in average fleet economy reduces total GHG emissions by 48% in year 2050 relative to the year 2000, and also leads to a drop in the number of gas stations, because more efficient vehicles reduce gasoline consumption. However, that very increase in fuel economy for conventional gasoline vehicles (including HEVs) makes other AFVs even less attractive, further suppressing their emergence. In sum, under the baseline (no action) scenario, promising AFV technologies cannot get over the tipping point: the reinforcing feedbacks that could lead to greater AFV adoption, more fueling infrastructure, lower prices, higher performance, and greater consumer awareness all work as vicious cycles that suppress AFV adoption.

Next, we present a scenario that aims to overcome the barriers that prevent consumer adoption of the plug-in electric vehicles (PHEVs and BEVs) in the baseline scenario. Here we introduce tax incentives ($5,000/vehicle) and manufacturer subsidies ($5,000/vehicle), lowering the high prices of HEV, PHEV, and BEV vehicles, and launch an aggressive marketing campaign ($250M/year) to build consumer awareness of hybrid and electric vehicles (Figure 10).

The result is a market still dominated by HEVs, but which now also sees significant consumer adoption of PHEVs. Subsidies make PHEVs and BEVs more attractive, and the marketing campaign builds consumer acceptance of these vehicles. These actions boost adoption of PHEVs, but not BEVs: while PHEVs use the ubiquitous gasoline fueling infrastructure when an electric charge point is not available, the lack of publicly accessible charging infrastructure severely limits the effective range of BEVs. The resulting range anxiety has a strong negative effect on the utility of BEVs to consumers, suppressing BEV adoption despite substantial incentives and marketing effort. GHG emissions in 2050 fall by 51% in 2050 relative to the year 2000, a marginal improvement over the baseline reduction of 48%. Further, the policies required are costly, with automakers losing $550 billion cumulatively by the year 2050 due to the cost of subsidies, and governments spending cumulatively $1.8 trillion by the year 2050 in tax incentives.

The next scenario aims to overcome the infrastructure chicken-egg dynamic for BEVs. We maintain the subsidy and marketing policies in the second scenario and add a program of government-funded charging station construction (1,000 charging points per year) and incentives for infrastructure deployment by private firms ($500 per charging point). We also introduce a carbon price that increases linearly to $300/tCO$_2$ by the year 2050 (Figure 11); such a tax would raise gasoline prices by approximately $2.63/gallon ($0.69/liter) by 2050. The results show a market in the early stages of a widespread transition away from conventional gasoline vehicles. Sales of HEVs grow rapidly, then peak and decline around 2035 as consumers switch to PHEVs and BEVs. The government-sponsored infrastructure program and incentives kick-start the deployment of recharging stations. Freed from range anxiety, consumers become more willing to consider and purchase PHEVs and BEVs; as they do, the utilization and profitability of charge points rise, leading to an economically self-sustaining market for charging infrastructure. At the same time, the carbon price raises the cost of driving

Figure 10. EV Promotion Scenario.

gasoline powered vehicles, while growing adoption of PHEVs and BEVs drives their prices down through scale, R&D, and learning by doing, further boosting their attractiveness and market share. With these policies the market for electric vehicles is able to cross the tipping point so that the reinforcing feedbacks that previously suppressed demand now work as virtuous cycles of greater adoption, lower cost and higher performance, additional charging infrastructure, and still greater adoption. As the market shifts to electric vehicles, demand for gasoline falls, and with it, the number of gas stations.

GHG emissions by 2050 are now 59% below the year 2000 level. However, the strategy is even more costly, with automakers losing $850 billion per year cumulatively by the year 2050, and governments spending $2.2 trillion cumulatively by the year 2050 including tax incentives for vehicles and infrastructure.

These scenarios suggest that a widespread transition away to gasoline vehicles towards electric vehicles is possible by 2050, achieving a significant reduction in GHGs. However, doing so requires significant initial investment in policies to increase AFV affordability, fueling infrastructure, and consumer awareness and willingness to consider these vehicles. The challenge for users is to explore how they can achieve market outcomes that are sustainable both ecologically and economically; that is, how to achieve the deep cuts in GHG emissions needed to mitigate climate change by creating the conditions for a profitable and healthy automotive industry, and associated fuel supply chain and delivery infrastructure.

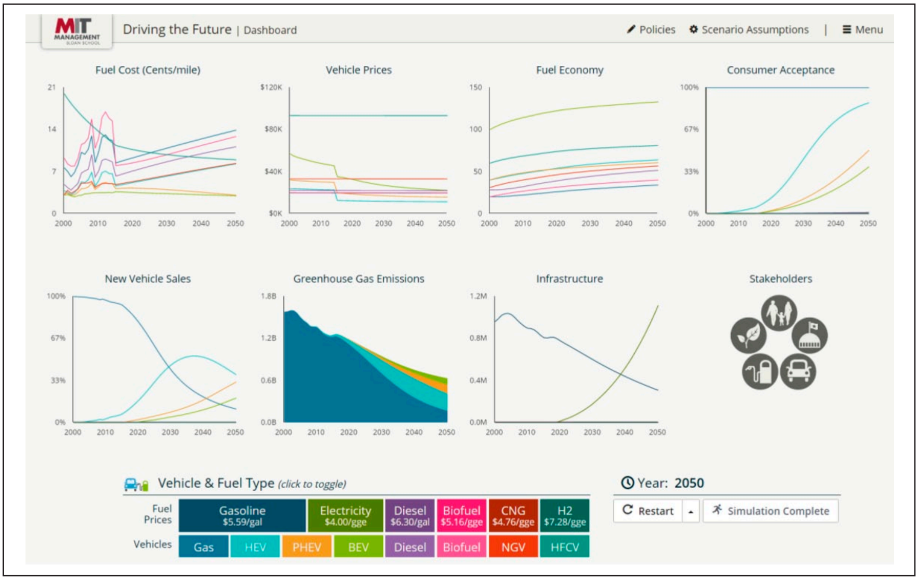

Figure 11. EV Infrastructure Scenario.

Simulator Use

We now describe how *DtF* can be used to facilitate learning about AFV diffusion dynamics in group settings. Although the simulator can be used by individuals at any time through the web interface, our experience suggests group play in which two or three people work together on the same scenarios can create a stimulating environment for learning. Putting participants in a situation in which they must agree on policies and strategies stimulates discussions that foster the development of shared knowledge and improved mental models. We first describe a general structure for *DtF* simulation workshops. We then describe results we have observed running workshops with a range of audiences.

Workshop Design

Simulation workshops using *DtF* can be run successfully in 60-120 minutes, with 4-100 participants. The only materials needed for the workshop are a sufficient number of computers or tablets with internet access to provide one device for each team of participants. No prior preparation from participants is needed. The workshop can be run by a single instructor, although assistants can be helpful to answer questions with larger groups. Table 5 outlines a workshop design we have found effective.

Results from Workshops

We have facilitated workshops using the protocol above with three distinct groups of participants. First, we have run the workshop with approximate 30 attendees at the International System Dynamics Conference (ISDC), the annual conference for researchers and practitioners in the field of System Dynamics. Second, we have run three workshops for approximately 100 students each in a graduate-level class, 'Laboratory for Sustainable Business' (S-Lab), at the MIT Sloan School of Management. Third, we have run two workshops with executives from two different major automobile manufacturers, each with approximately 20 participants.[6] In each case, the participants possessed a high degree of domain knowledge relevant to understanding the dynamics of AFV diffusion. The ISDC participants were familiar with systems thinking and the use of simulation models for policy analysis. The S-Lab students at MIT, including MBAs and graduate students in urban planning, engineering, and public policy, had strong interests in sustainability issues. The automaker executives, in contrast, possessed detailed domain knowledge about vehicle technologies and regulatory compliance issues. We nevertheless observed similarities in the approach to problem solving and lessons learned across these groups.

As in any game, participants' first game takes more time than subsequent games as they go through a personal learning curve in which they discover how to make decisions, what outputs are available, and how to interpret the graphs and tables available to them. Play accelerates quickly, however, with participants soon focusing their attention on the substance of the scenario and results instead of the game interface.

Participants typically begin with policies that have been implemented in reality and at modest scales, for example, tax incentives and marketing campaigns to build awareness of AFVs. They discover that these policies are ineffective (as shown by the illustrative scenarios in Section 4). In particular, participants often launch policies including subsidies, price reductions, and marketing campaigns, finding that, after a few years, AFV market share is rising. They also observe the rising costs of their policies (for example, the cost of vehicle subsidies and tax breaks rises with AFV sales). Many then cut back the subsidies and incentives, reasoning that the AFV market will now be self-sustaining. Instead, AFV sales often fall and the market fails to develop. In this fashion, participants discover for themselves the dangers of the "sizzle and fizzle" pattern so often observed in prior attempts to introduce AFVs.

After several rounds of game play, participants frequently comment about the difficulty of creating a self-sustaining AFV market. The large array of information available to them in the simulation interface enables them to discover the causes of these results for themselves, including: the long delays in fleet turnover, which slows the accumulation of experience with and social exposure to AFVs, slowing adoption; the importance of building fueling/charging infrastructure; the way in which efficiency improvements for conventional gasoline vehicles helps cut GHG emissions but also reduces the relative attractiveness of AFVs; and so on. They also commonly discover that the short-run costs of the policies needed to create a self-sustaining AFV market are high, and conclude that coordination across multiple stakeholders, including

Table 5. Simulation Workshop Structure.

Sequence of Events	Description
1. Introduction	• The instructor introduces the sustainability challenges associated with the US automobile fleet, such as fossil fuel consumption, greenhouse gas emissions, and urban air pollution. Participants are then tasked with the challenge of implementing policies and strategies that make the US automobile fleet more sustainable by the year 2050, taking the economic, environmental, and social consequences of those decisions into account.
2. Demonstration of *Driving The Future* Simulator	• The instructor introduces the *DtF* interface. First, the instructor ensures that all participants are able to open the simulator and navigate to the dashboard. • Next, the instructor demonstrates how to use *DtF* to simulate scenarios. The instructor first leads the participants in simulating a base case with no policy or strategy interventions. The instructor then demonstrates a simple policy, such as the introduction of tax incentives for HEV adoption. Faster diffusion is observed, but at considerable cost to the government, highlighting trade-offs across stakeholder groups.
3. Policy Analysis Task	• Participants are now ready to undertake their own experimentation. When workshops have many participants, we find it effective to divide the group into several blocs, each representing a different stakeholder. For example, the group can be divided into blocs representing: (i) electric vehicle manufacturers; (ii) oil companies; (iii) environmental non-profits; and (iv) the government treasury. Participants are tasked with identifying a mix of policies and strategies that best satisfy the objectives of their stakeholder group. • We encourage participants to iterate through scenarios rapidly, making incremental changes in response to strengths and weaknesses they identify in their previous scenarios. Learning opportunities emerge from observing the results of many scenarios rather than laboring over the details of fewer scenarios.
4. Debriefing	• As the end of the workshop approaches, the instructor leads a debriefing discussion with the participants, reconciling the findings of participants, and reinforcing key insights about AFV diffusion. • Participants are invited to contribute the mix of policies and strategies they consider best given the stakeholder group they represent, considering key metrics such as GHG emission reductions and total cost to automakers and governments. • Subsequent discussion regarding the extent to which the strategies chosen by each group are aligned or in conflict highlights the opportunities and challenges involved in implementation.

automakers, fuel providers, and federal and state governments, is likely to be required to generate sufficient resources to move the industry over the tipping point.

Participants also commonly discover that the displacement of gasoline-powered vehicles with AFVs such as BEVs does not enhance GHG emissions reductions if the power for the BEVs is generated from fossil fuels, as is typical in most of the US today. They discover that the market for AFVs and alternative fuels must coevolve with the transition from fossil fuels to renewable, low-carbon energy sources for the electric grid, leading to discussion of the potential synergies and barriers to that transition, including how the batteries in BEVs could also be used as storage to buffer the electric grid against variations in load and power production as intermittent renewables like wind and solar become more important.

Our observations from these workshops suggest that *DtF* is easy to use, enjoyable and effective in developing insights regarding AFV diffusion. Participant evaluations of the experience were highly positive, including:

> "The simulator is great! Great interface, super modern. I would have liked to have more time to play with it."

> "I love the ability to manipulate the scenarios and see how different policies interact".

Evaluation of Simulator Effectiveness

To move beyond anecdotal information about its effectiveness, we carried out an evaluation of the simulator with a broader sample of American users via Amazon's *Mechanical Turk* (MTurk) online workforce. The goal of this evaluation was to explore: (i) whether measurable learning could be observed as a result of using *DtF*; and (ii) whether learning outcomes were superior as a result of using an interactive simulator compared to more conventional learning methods. We implemented a three-group pre-test post-test experimental design (Tiwari, 2016). Group 1, the control group, was assigned the task of reading a PDF report about the results of the *DtF* simulator, including actual screenshots from 5 structured scenarios, conveying the same insights about AFV diffusion that are obtained from using *DtF* but delivered in a conventional format. Group 2 was assigned the task of exploring those same 5 scenarios interactively using *DtF*, but were not provided any written interpretation of the results of those scenarios. Group 3 was provided both the DtF simulator as in Group 2, and the written interpretation of results provided to Group 1.

A sample of 210 participants were recruited from MTurk, with 70 participants randomly assigned to each experimental group. Each participant received a $5 payment for successful completion of their assigned task, including pre-test and post-test surveys. We took various steps to ensure the quality of responses, including: restricting participation to MTurk workers with at least 95% reputation score and completion of at least 500 prior MTurk tasks (Peer, Vosgerau, & Acquisti, 2014); restricting participation to MTurk workers whose IP addresses were verified to be in the United States; and the inclusion of attention check questions in the pre-test and post-test. The

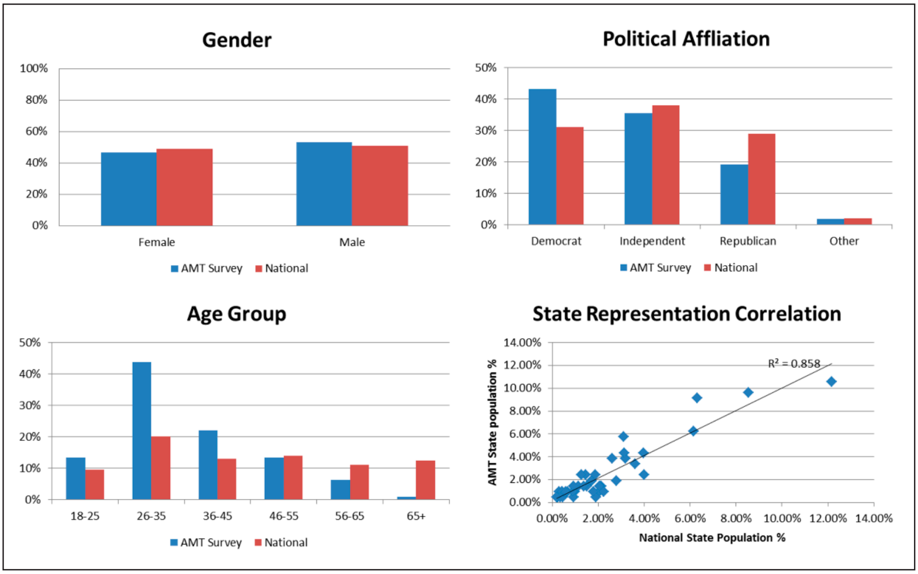

Figure 12. MTurk Participant Demographics.

demographics of our sample are broadly representative of the US population (Figure 12), although tending to be younger (consistent with prior MTurk studies, e.g. Berinsky et al., 2012), and somewhat more politically progressive. Pre-test questions indicate a high degree of awareness about climate change, with 70% of participants answering that it is 'very important' or 'extremely important' for the United States to reduce GHG emissions, roughly consistent with public opinion as measured in nationally representative samples of US registered voters (Leiserowitz, Maibach, Roser-Renouf, Rosenthal, & Cutler, 2017). However, participants were less aware of available AFV technologies. Although the vast majority of participants stated being extremely familiar with conventional GAS vehicles, most respondents were only moderately familiarity with HEVs, PHEVs and BEVs, and not familiar at all with HFCVs.

Participants completed their assigned tasks individually. While participants were all instructed to spend 35-50 minutes on the task, and compensated accordingly, significant variation occurred in how long each group spent completing their task. Group 1 spent an average of 34 minutes on the report-only task, with a standard deviation of 13 minutes. Group 2 spent an average of 74 minutes on the simulator-only task, with a standard deviation of 38 minutes. Group 3 spent an average of 101 minutes on the simulator + report task, with a standard deviation of 36 minutes. Participant comments suggest that for some people the longer time was necessary to complete the simulator task, while others voluntarily used *DtF* longer than necessary so they could explore their own scenarios.

We assessed participant learnings with pre-test-post-test questions in a variety of formats. For example, we asked participants to what extent they agreed with the

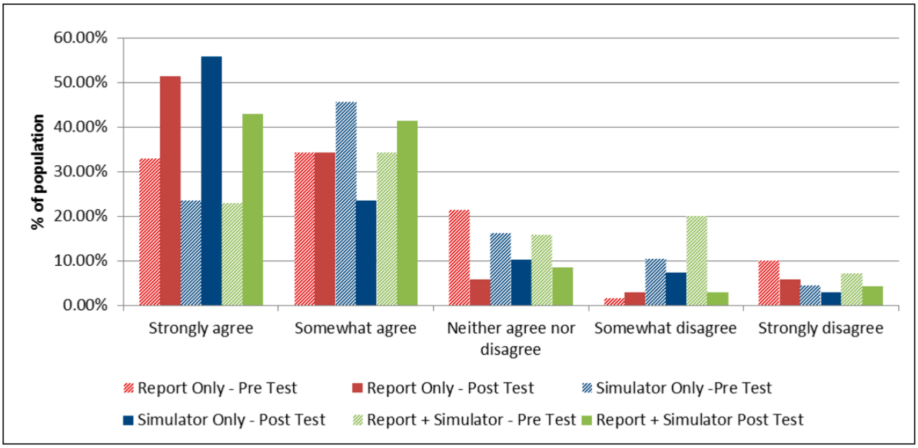

Figure 13. To What Extent Do You Agree That Government Policy Interventions Are Needed to Build a Viable Market for AFVs?

statement that government policy interventions are needed to build a viable market for AFVs (Figure 13). Here we observe a substantial increase in the percentage of respondents that strongly agree with this statement upon completion of their task across all groups, increasing from 31% to 51% in Group 1, 22% to 56% in Group 2, and 22% to 42% in Group 3, statistically significant at $p < 0.05$ in each case.

We also asked participants how they would allocate funding to promote each individual vehicle platform across a range of possible allocation policies. The HEV results are particularly interesting (Figure 14), because right answers (Options A, B and D) and wrong answers (Options C, E, F and G) are well defined due to the fact that HEVs refuel with gasoline rather than charge with electricity. Here we see a statistically significant shift away from Options E and G towards Options A, B and D for both the groups that used simulator (Group 2 and Group 3), but not in Group 1 that read the report, where an increase in selection of Option G is observed, suggesting that both groups using the simulator developed a better understanding of these infrastructure dependencies (Tiwari, 2016).

Finally, we asked the MTurk participants that used the simulator to evaluate their experience using *DtF* on a 5-point Likert scales ranging from "strongly disagree" to "strongly agree". 96% of participants strongly agreed or somewhat agreed that "*the simulator enabled you to develop an improved understanding of the AFV market and policy levers*" (Figure 15). Similarly, 94% strongly agreed or somewhat agreed that *"the simulator can provide a better learning opportunity than traditional reports and PowerPoint presentation methods"* (Figure 16).

Taken together, the results of the MTurk evaluation provide compelling evidence that *DtF* is effective at helping users learn about the dynamics of AFV diffusion, and potentially more effective than conventional learning methods. Continued evaluation of *DtF* and other management flight simulators is a key opportunity for future work,

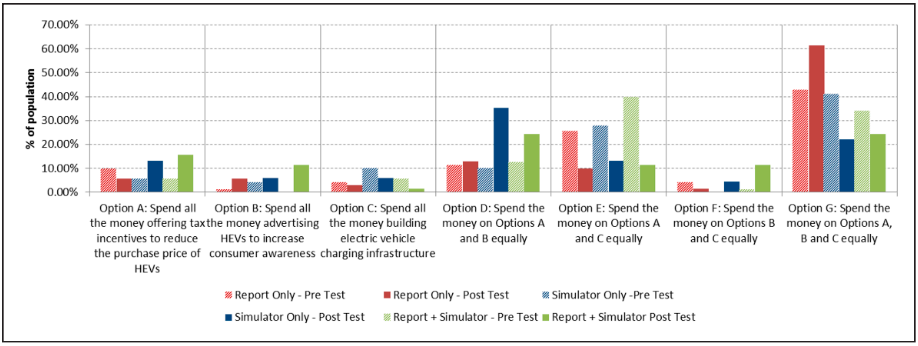

Figure 14. Assume That You Are the Car Czar: How Will You Spend Money to Promote HEVs?

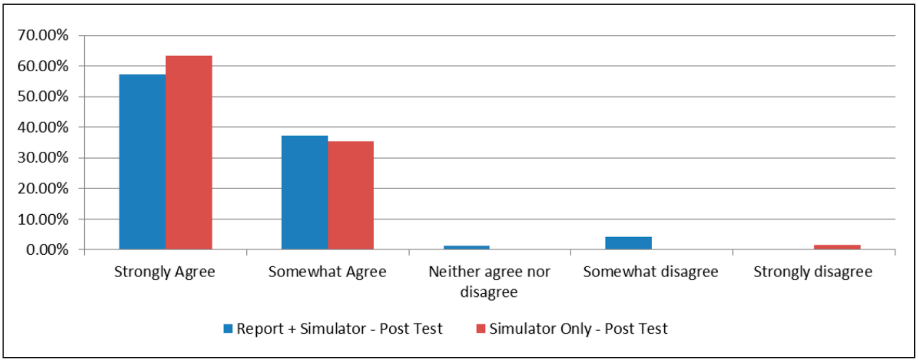

Figure 15. To What Extent Do You Agree That The Simulator Helped You Develop an Understanding of the AFV Market and Policy Levers?

for example, exploring to what extent these lessons learned persist over time (e.g. the user's mental model has changed permanently), and whether these learning result in a superior real-world decision-making ability.

Conclusion

Driving the Future is a free, web-based management flight simulator designed to help people learn about the challenges of creating markets for alternative fuel vehicles that are sustainable both ecologically and economically. The simulator embeds an empirically grounded, behavioral, dynamic model portraying multiple automobile and fuel types, fueling infrastructure, and consumer choices, and enables users to rapidly experiment with a wide array of policies and assumptions through 2050. The simulator provides users with immediate feedback on the likely impacts of their decisions, enabling people to learn for themselves about the dynamics of the industry and to

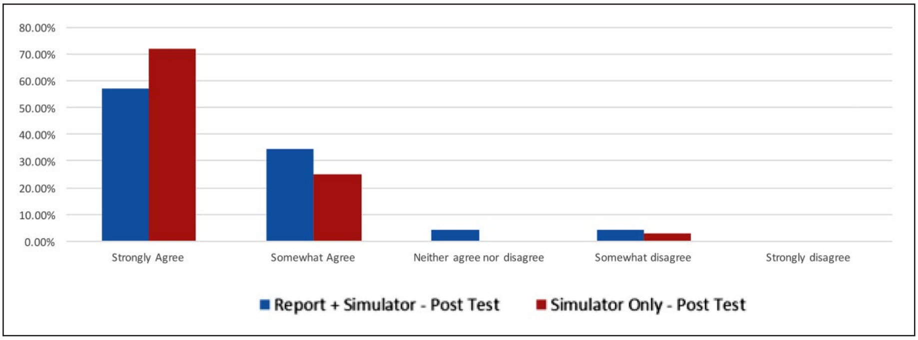

Figure 16. To What Extent Do You Agree That The Simulator Provides a Better Learning Opportunity Compared with Traditional Reports and PowerPoint Presentations?

discover policies that can lead to the emergence of a self-sustaining alternative vehicle industry.

The simulator does not favor specific outcomes – users are free to promote a wide array of alternative vehicles, including vehicles powered by electricity, diesel, hydrogen, natural gas, biofuels, and hybrids, and can implement any mix of strategies and policies they choose. Although future technology pathways in the US automotive market are inherently uncertain, experimentation with an interactive market simulator allows users to explore for themselves the challenges and opportunities that exist for the development of sustaining markets for AFVs. *Driving the Future* has been used successfully in a range of settings, from individual users, to university teaching about sustainability issues, to workshops with senior executives from leading automakers.

Looking forward, further developing the capabilities of the *DtF* model is an ongoing opportunity. Calibration of the model to date has depended largely on expert judgement, due to the very low market shares of all AFV platforms to date. As more data become available, model parameters and relationships can be refined. Emerging automotive technologies such as autonomous (self-driving) vehicles and business model innovations such as shared mobility services also have the potential to alter how automobiles are used in the United States, creating both opportunities and challenges for policies to develop sustainable transportation systems. Adding these emerging technologies to the *DtF* model is a key opportunity for future work, as is the adaptation of *DtF* for other geographic markets. Both the *DtF* model and online user interface must evolve over time to respond to these developments and maximize learning opportunities for users. Given the pressing need to develop sustainable transportation, it is imperative that research not only explores how best to facilitate the development of improved mental models about AFV diffusion, but also translates that learning into testable real-world experiments and evidence-based policy and strategy improvements.

Appendix 1: Model Sensitivity Analysis

To test the sensitivity of the model to parametric assumptions, we undertake multivariate Monte Carlo analysis for key sub-models. In the sensitivity analyses that follow, we define distributions for each of the parameters in the sub-model, and then simulate 1,000 runs of the model, drawing parameters for each model run using Latin hypercube sampling.

First, we explore the model's sensitivity to utility function coefficients. We assume a normal distribution for all utility function coefficients listed in Table 3, with 20% standard deviation, limited to a span of ± 2 standard deviations from the reference values (Figure 17). These simulations show that while significant variability exists in the specific market share of each vehicle platform over time, the overall pattern of behavior is unchanged.

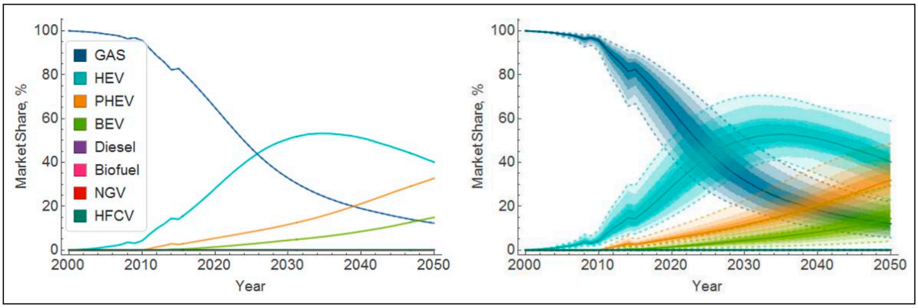

Figure 17. Reference and sensitivity runs for utility function parameters.

Second, we explore the model's sensitivity to uncertainty in consumer consideration parameters. We assume normal distributions for the parameters that define the strength of social exposure and marketing efficiency, with 20% standard deviation and a span of ± 2 standard deviations from the reference values (Figure 18). The greatest variability is observed in the trajectory of the HEV platform. The rate of HEV adoption is strongly conditioned by the growth of consumers' willingness to consider this new type of vehicle, whereas PHEV and BEV adoption is also conditioned by vehicle cost, range/performance, and charging infrastructure availability.

Third, we explore the model's sensitivity to uncertainty in parameters governing deployment of refueling infrastructure. We assume a uniform distribution for the parameter defining the sensitivity of new station construction to station utilization, with a span of ± 40% of the baseline value. We also assume a normal distribution for target profitability with 20% standard deviation, restricted to ± 2 standard deviations from the reference values (Figure 19). Here we observe significant growth and variation in the adoption of PHEV and BEVs (largely at the expense of conventional hybrids). Higher BEV and PHEV adoption occurs when entrepreneurs are assumed to build new charging stations even when utilization of existing stations is low, because the more extensive network of charge points lower range anxiety and the costs associated with the search for charge points, ultimately increasing adoption and charge point utilization.

Finally, we explore the model's sensitivity to the strength of technology change, assuming uniform distribution of the strength of all learning curves with the span of ± 40% of the

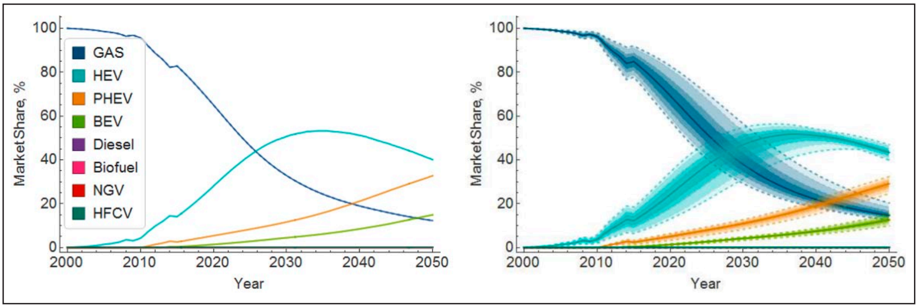

Figure 18. Reference and sensitivity runs for consumer consideration parameters.

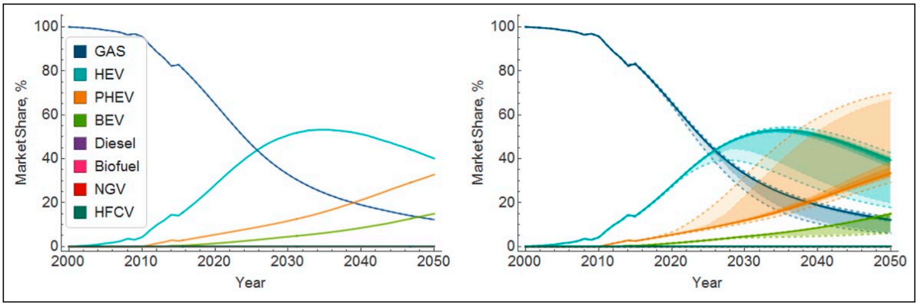

Figure 19. Reference and sensitivity runs for infrastructure adjustment parameters.

reference values (Figure 20). Here we observe the greatest variability in the diffusion of the more advanced PHEV and BEV platforms, which are more expensive initially and have greater opportunity for improvement as a result of learning.

Overall, the simulation results are robust to significant variation in the critical parametric assumptions.

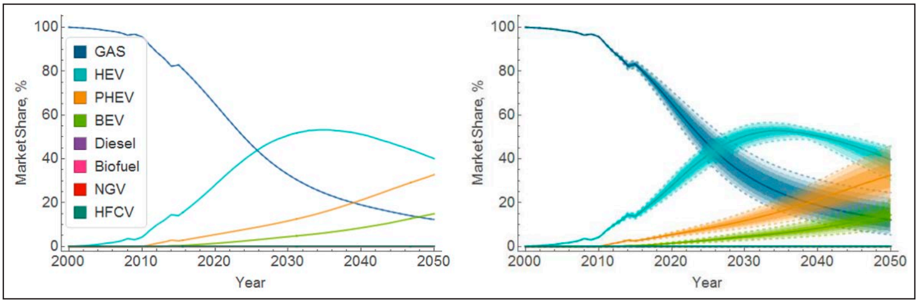

Figure 20. Reference and sensitivity runs for OEM learning parameters

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Notes

1. We use the units 'miles per gallon' (mpg) that are standard in the United States, recognizing that this inverse measure of vehicle fuel efficiency has been observed to result in systematic misperceptions of vehicle fuel efficiency (Larrick & Soll, 2008). Fuel economy in mpg = 235.2 / fuel economy in L/100km.
2. The Trump administration recently announced that it will review the stringency of the CAFE targets, which is expected to result in a weakening of fuel economy standards for cars and light trucks (DeCicco, 2017), such as freezing the CAFE target at the 2021 level for years 2021-2025.
3. While the US vehicle fleet size, average vehicle life, and annual rate of new vehicle sales vary modestly year-on-year (USDOT, 2015), the US market is mature, with little change in total fleet size. The assumption of constant fleet size is also helpful for learning about the fundamental dynamics governing AFV diffusion. The model is easily adapted to an emerging economy such as India or China where growth in the total fleet is significant.
4. However, as conventional gasoline vehicles have constituted nearly 100% of the on-road vehicle fleet for nearly a century, we assume that all buyers maintain full consideration of gasoline vehicles.
5. As of this writing data are available through 2015. As new data become available, we will update the simulator so that the user begins at the current time with the most recent available data.
6. We invited the two auto firms to participate in a single workshop, but both declined, citing concerns over proprietary information.

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