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Essays on the Dynamics of Alternative Fuel Vehicle Adoption: 
Insights from the Market for Hybrid-Electric Vehicles in the 
United States

by

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Abstract

Despite growing energy security and environmental concerns about dependence on oil as a 
transportation fuel, gasoline remains the overwhelmingly dominant fuel used by the US automotive 
fleet. Numerous previous efforts to introduce alternative fuel vehicles (AFVs) fueled by hydrogen, 
biofuels and electricity have failed, and significant barriers to a rapid transition to AFVs remain. 
One technology that has achieved considerable success in the US is the gasoline hybrid-electric 
vehicle (HEV), which integrate gasoline and electric powertrain components to significantly 
improve the efficiency of gasoline use. Since their introduction in 1999, over 2 million HEVs have 
been sold in the US, with more than 30 HEV models available to consumers today. In this 
dissertation I explore the dynamics of adoption of HEVs, examining factors influencing consumer 
adoption of HEVs to date, and, looking forward, the role of HEVs in the emerging market for plug-in 
electric vehicles (EVs).

In Essay 1, I examine the market for the iconic Toyota Prius HEV. While more than 1 million 
Prius vehicles have been sold in the US, this market has been characterized by long wait lists at 
Toyota dealerships, evidence of supply constraints influencing the diffusion process. The 
innovation diffusion literature says relatively little about supply constraints, representing diffusion 
as a fundamentally demand-side process. Here I develop a model of innovation diffusion that 
incorporates production capacity and dealer inventory. Inclusion of supply constraints improves 
the explanatory power of the model in the Prius case, and demonstrates that the failure to model 
supply constraints can bias diffusion model parameter estimates.

Essay 2 is motivated by the observation that Prius sales are not uniform geographically. 
Sales of the Prius have clustered in regions such as the West Coast, around Washington DC and
through New England, with many fewer sales of the Prius in the south and mid-west. I propose two alternative hypotheses to explain the emergence of these clusters: 1) contagion through consumers' social networks; and 2) market heterogeneity that influences consumers' adoption thresholds. I develop a model of spatial innovation diffusion that captures spatial information generation between regions and consumer discrete choice between technologies. I find that in the Prius case, adoption clustering is explained by social contagion at the local level, which amplifies heterogeneous adoption thresholds.

In Essay 3, I explore the future role of HEVs as a transitional technology in the emerging market for plug-in EVs, which hold the potential to achieve deep cuts in oil consumption and greenhouse gas emissions. The technology strategy literature suggests that hybrids technologies help the transition to radical technologies, accumulating producer learning, consumer familiarity and complementary assets that spillover to the radical technology. However, EVs remain expensive, have a limited electric range and lack a ubiquitous recharging infrastructure, while HEVs are relatively cheaper and refuel from the existing gasoline refueling infrastructure. I develop a model of hybrid and electric vehicle diffusion with multiple competing entrants, finding that the smooth transition from HEVs to EVs is possible but not assured, identifying public policy and firm strategy decisions that have the potential to accelerate this transition.

Thesis Supervisor: John Sterman
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Abstract
Despite the extensive literature examining the diffusion of innovations, few have considered the effect of supply constraints on the diffusion process. Here I extend existing theories of diffusion under supply constraint to capture price dynamics, accounting for both waiting lists in the presence of excess demand, and discounting in the presence of excess supply. The model is tested against the case of the diffusion of the Toyota Prius hybrid-electric vehicle in the United States, quantifying the relative contribution of marketing and word-of-mouth to the development of familiarity with the Prius, and explaining both persistent waiting lists over many years and more recent discounting against the Manufacturer's Suggested Retail Price (MSRP). The inclusion of endogenous wait lists and discounting significantly improves model explanatory power and alters the contribution of marketing and word-of-mouth to the diffusion process compared to models lacking supply constraints. Policy analysis reveals synergies between the strategy that maximizes Toyota's profits and societal energy policy goals.
1. Introduction

When launching a new product, manufacturers face an inherent challenge of forecasting uncertain future demand and providing sufficient product capacity to match supply accordingly. Lead times and costs for capacity acquisition in manufacturing are often substantial, so firms need to plan ahead to ensure they have sufficient installed capacity on hand to satisfy expected demand, without producing so much that they cause excess inventories and holding costs. In light of this forecasting challenge, it is surprising that an apparent gap exists between the operations literature on production capacity planning and the considerable marketing literature on innovation diffusion (Ho, Savin et al. 2002). Much of the operations management literature has focused on flexibility and robustness in capacity planning, allowing firms to respond to a range of future demand scenarios (for example Fine and Freund (1990), Graves and Tomlin (2003), Gupta, Gerchak et al. (1992) and Li and Tirupati (1995)). On the demand side, the innovation diffusion literature provides insights about factors that influence the uptake of new products, but says relatively little about the role of product availability. The seminal Bass model (Bass 1969) identified forces of innovation and imitation to explain the often-observed S-shaped diffusion pattern. Since then, numerous extensions to the Bass model have been introduced to understand the effect additional decision variables have on the diffusion process, such as prices (Robinson and Lakhani 1975), multiple product generations (Norton and Bass 1987) and dynamic adopter populations (Mahajan and Peterson 1978) [For more detailed reviews of this literature see (Mahajan, Muller et al. 1990; Geroski 2000; Peres, Muller et al. 2010)]. However, a widespread assumption in this literature is that diffusion is as an exclusively demand-side phenomenon, driven by social processes such as marketing and word-of-mouth. Assuming that an unlimited quantity of the product is available for adoption necessarily ignores the potential for the available supply of a product to influence diffusion of that product, and vice-versa.

The impact of supply constraints on new product diffusion is readily observable in recent product launches. Waiting lists emerged soon after the launch of new technologies such as Apple's iPad tablet computer, Sony's Playstation 3 game console, Harley-Davidson motorcycles and Toyota's Prius hybrid-electric vehicle, as demand from eager consumers exceeding the available product supply (Automotive News 2004; Sabbagh 2006; AppleInsider 2010). In the presence of supply constraints, potential sales are either delayed, as customers are forced to wait to adopt, or lost completely as customers become frustrated. A small literature has considered the effect supply constraints have on innovation diffusion. Jain, Mahajan et al. (1991) extended the Bass model to
integrate supply with demand by introducing a stock of Waiting Applicants, applying this model to
the diffusion of landline telephone connections in Israel, assuming customers wait a fixed time
before their order is fulfilled. Ho, Savin et al. (2002) and Kumar and Swaminathan (2003) extend
Jain et al.’s model by capturing the potential for lost customers due to wait-listing, identifying
circumstances where stockpiling inventory prior to the product’s introduction may outperform a
myopic sales strategy. However, important questions remain about how supply constraints
influence new product diffusion, including how supply constraints influence the price the firm
receives for its product, and how supply constraints influence the spread of information about the
product through word-of-mouth. Furthermore, limited empirical application of models of
technology diffusion under supply constraints has been undertaken to date.

Here I introduce and estimate a formal diffusion model incorporating limited production
capacity, endogenous waiting periods and dynamic pricing behavior on an example of new product
diffusion that has been characterized by supply constraint: the diffusion of Toyota’s Prius hybrid-
electric vehicle in the United States. First, I develop a model of technology diffusion that captures
price feedbacks in the presence of supply constraints, and multiple word-of-mouth channels
including the possibility of word of mouth from prospective customers on the wait list. Consumer
choice is explicitly represented using a logit model, allowing the examination of the impact of
changes in technology attributes and policy instruments in the adoption context. Second, I use
novel data sources to quantify the length of waiting lists over time. Third, I estimate diffusion
parameters for this model based on the case of the Toyota Prius. As expected, both marketing and
word-of-mouth are significant in developing consumer familiarity. Compared to traditional Bass-
style models without supply constraints, the endogenous treatment of waiting time and dynamic
pricing significantly affects the values of the marketing and word-of-mouth parameters. Ignoring
supply constraints in diffusion models when influential may result in systematic bias in estimates of
diffusion parameters. Finally, I use the model to explore policies that maximize Toyota’s profits
from the Prius platform, finding alignment between profit maximization and societal goals to
reduce oil consumption and greenhouse gas emissions.

2. Supply Constraints and Waiting Lists

Supply constraints are a reality in the manufacturing of most durable goods, limiting the
speed with which production capacity can be adjusted. Numerous delays exist in the process of
capacity expansion, including perceiving the need for additional capacity, hiring new staff and
investing in new manufacturing equipment. Similarly, delays in downsizing production may exist
due to contractual obligations with staff and suppliers. As a result, a firm’s production is usually less responsive to change than the rate at which consumer demand for the firm’s product can vary, with critical strategic implications. In complex and dynamic markets where demand evolves quickly, managers are unlikely to anticipate the saturation of the market, resulting in excess capacity and potentially catastrophic losses, as observed in the case of fiber optic equipment maker JDS Uniphase (Sterman, Henderson et al. 2007). Even when the dynamics of the market are relatively slow, both excess supply and excess demand are costly for firms. When excess inventories exist, firms incur inventory-holding costs, motivating discounts or rebates to stimulate sales. When demand exceeds supply, potential sales are delayed or lost to competitors (Urban et al. 1990).

Despite this, supply constraints alone are not a sufficient explanation for the existence of waiting lists. Microeconomic theory suggests that when excess demand exists, firms should simply raise prices to maximize profits and clear the market, sometimes disparagingly described as ‘price gouging’. For waiting lists to arise, firms must be unwilling or unable to raise prices enough to clear the market, and customers must be unwilling or unable to switch to an alternative product. The Mental Accounting literature provides arguments for why firms might not wish to raise the price of their product despite surplus demand. If firms believe that consumers know the fair value or ‘reference price’ for their product, customers may perceive ‘transaction disutility’ if they are charged more than that reference price (Thaler 1985), such as past prices for that product, the price of competitors’ products or the cost of manufacturing the product (Bolton, Warlop et al. 2003). Second, firms may wish to maintain an ongoing relationship with their customers and not risk losing them by raising prices (Thaler 1985). For example, much of the revenue video game console makers earn comes not from the sale of game consoles but from the sale of games and from licensing their platform to software developers (Evans 2003), providing strong incentive to keep console prices low and grow the installed base of users. These arguments may be particularly salient for the launch of novel products where consumers have yet to form their opinion about the product, and an installed base of that product does not yet exist.

Numerous situations exist in which customers may be unable or unwilling to switch to an alternative when their desired product is in short supply, requiring them to join the waiting list for that product. The simplest case occurs when the product in question is the only product of its type available, either because it is the first product available in a new market or because the producer has been able to protect its product against imitation (Teece 1986). Even if alternatives exist, consumers may be unwilling to switch. First, consumers may want a particular product because of
the signal it sends about the consumer's social status. For example, hybrid-electric vehicles with distinct features such as the Toyota Prius are widely perceived as sending a strong signal about the driver's preference for environmental stewardship. Second, the existence of network externalities may make one product more attractive than its competitors, if an installed base of that product already exists (Katz and Shapiro 1985; Farrell and Saloner 1986; Arthur 1989; Katz and Shapiro 1994). For example, a consumer is likely to prefer the same video game console as her friends to facilitate the sharing of games, even if she must wait to purchase that console. Third, the fact that waiting lists exist for a product may itself be influential in sustaining demand for that product. Scarcity makes opportunities seem more valuable, so consumers may be more attracted to those products that are hardest to get (Bikhchandani, Hirschleifer et al. 1998; Cialdini 2007). Further, when consumers are uncertain about what decision to make, such as whether or not to adopt a new technology, consumers often look to others for guidance about what the correct decision to make is (Cialdini 2007). The existence of a waiting list for a product provides social proof to the decision-maker that others have already decided to adopt that product.

Waiting lists may also influence the extent to which social contagion drives consumers' acceptance of the product. It is generally accepted that the actions of new product adopters influence the opinions of potential adopters, motivated by concerns such as social learning under uncertainty, social-normative pressures, competitive concerns and network effects (Bikhchandani, Hirschleifer et al. 1998; Van den Bulte and Lilien 2001). The magnitude of this social contagion effect, often referred to as word-of-mouth, is usually expressed as a function of the installed base of adopters, as in the Bass model's coefficient of imitation, \( q \). In contrast, I propose that potential adopters, adopters and those on the waiting list may all generate word-of-mouth, but to differing extents, and with either positive or negative valence. Whereas adopters have first-hand experience with the product, potential adopters can only pass on information they themselves have learned through word-of-mouth, the media and other sources (e.g., social media); the likelihood they will do so, and the persuasiveness of such information is likely to be less than that generated by adopters. Thus, I hypothesize that the coefficient of word-of-mouth from adopters will be greater than the coefficient of word-of-mouth from potential adopters. Indeed, for a reinforcing feedback to exist this must be the case, otherwise socialization from the adopted and potential adopters combined would be constant. The strength and valence of word-of-mouth that might be generated by waitlisted buyers remains an open question. The behavioral view of scarcity and social proof suggests a positive valence. For example, being on the wait list for a Harley-Davidson conveyed considerable status to buyers, who could then tell their friends, buy merchandise and even tattoo
the company name on their body (Peak 1993). In contrast, the classical view of queuing, emphasizing the frustration associated with waiting (Larson 1987), suggests a negative valence, because the experience of having to wait for the product sours the views of those on the wait list so that they generate unfavorable word-of-mouth.

The theory developed here highlights the dynamic and asymmetric interplay that exists between demand and supply in the context of innovation diffusion. When supply constraints exist the rate of sales of a new product depends not only on consumer demand but also on the available supply of the product, the preferences of consumers and the pricing strategy of the firm. In the rest of this paper a model I develop a formal model that implements this theory, and test it in the context of the diffusion of the Toyota Prius hybrid-electric vehicle in the United States.

3. Case Study: Diffusion of the Toyota Prius Hybrid-Electric Vehicle

Over the past decade, the Toyota Prius hybrid-electric vehicle (HEV) has become an icon of fuel efficiency, and a status symbol for environmentalists and celebrities alike. HEVs achieve improved fuel economy and reduced greenhouse gas emissions by combining a conventional internal combustion engine with an electric powertrain. Fuel savings result from various technological advances, including the ability to capture wasted energy through regenerative braking, the ability to temporarily switch off the engine whenever the vehicle is stationary, and the complementary performance attributes of the gasoline engine (long range) and electric motor (low-end torque and energy efficiency). However, the incremental cost of implementing a hybrid-electric powertrain in a passenger automobile has been estimated at almost $5,000 (Bandivadekar, Bodek et al. 2008), though it may be falling through learning and scale economies.

The 2-seat Honda Insight was the first HEV introduced to the United States (in 1999). The Prius, introduced in July 2000, rapidly overtook the Insight, with cumulative US sales surpassing 1 million units in 2011 (WardsAuto 2011). Studying the Prius market is particularly instructive, because the Prius accounts for more than 50% of all hybrid vehicles sold in the United States between 2000-2009, and Prius sales are highly correlated with sales of all other hybrid vehicles, ($r = 0.976, p = 0.000; Figure 1$). Sales have grown substantially since the Prius was first introduced (Figure 2), with monthly sales peaking in May 2007, with over 24,000 sold. Sales have trended downward since, reflecting the major contraction in light vehicle sales in the United States during the Great Recession, though Prius market share has continued to grow (Figure 3), except when Prius sales were heavily constrained in the aftermath of the 2011 Japan Earthquake. I hypothesize that several factors contributed to the sales dynamics observed, including: growing consumer
familiarity with the Prius resulting from Toyota's marketing spending (Figure 4) and word-of-mouth; the utility the Prius provides the consumer relative to its competition; and the supply available for purchase (Figure 5). A prominent feature in the history of the Prius in the United States has been the existence of persistent customer waiting lists for the purchase a new Prius (Automotive News 2004), suggesting that demand for the Prius has been greater than indicated by actual sales. Prius vehicles destined for markets worldwide are manufactured in Japan, and while Toyota has been able to expand assembly capacity, production has been limited by the availability of key components such as batteries (Greimel 2009). Data describing the length of the Prius waiting list is not readily available, as individual Toyota dealers managed Prius waiting lists. An important contribution of this work is to estimate the length of the Prius wait list over time, triangulating from multiple data sources. From US newspapers I collected the frequency per month of articles that make reference to a Prius wait list from 2000-2009 (inclusive), and whenever possible I also collected the wait list length estimate mentioned in the article, as two different measures of the wait list (Figure 6). These datasets are in broad agreement ($r = 0.673$, $p = 0.000$), showing a sustained and lengthy wait list from 2004-2007, with two smaller wait list outbreaks in 2001-2002 and 2008. A moving average (two months before and after) is applied to the Average Waitlist Estimate dataset to smooth out estimation noise, resulting in the dataset used for model estimation in the paper (Figure 7).
Figure 1: Annual Sales of Toyota Prius and Other Hybrid Models in the United States (HybridCars.com 2011)

Figure 2: Monthly Sales of the Toyota Prius in the United States (Automotive News 2011)
Figure 3: Market Share of the Toyota Prius in the United States
(Automotive News 2011)

Figure 4: Toyota Advertising Spending on Prius in the United States
(Kantar Media 2010)
Figure 5: Monthly Exports of the Prius from Japan to the United States
(Fourin 2010)

Prius Exports from Japan to the United States (vehicles/month)

Figure 6: Wait List Length Datasets

Average Estimated Length of Waiting List (Months)

Frequency of Newspaper References to Waiting Lists (number)

Correlation = 0.68
Fluctuations in demand relative to supply have been reflected in Prius prices as well as waiting lists. As is common in the automotive industry, customers do not usually pay the full MSRP for their vehicle, as dealers use incentives such as cash rebates and reduced-rate financing to manage their inventory. Data obtained from the Power Information Network (J.D. Power and Associates 2010) shows that when demand for the Prius is high, indicated by lower levels of inventory coverage, dealers are able to extract a high gross margin on each sale, charging at or close to the full MSRP for the vehicle. As vehicles spend more time sitting on dealer lots, the amount dealers are able to gross decreases as they offer discounts to encourage sales. Further, demand for the Prius has been influenced by the availability of numerous government incentives at the Federal, State and local level. In particular, the Federal Government’s ‘New Energy Tax Credits for Hybrids’ scheme provided tax credits of up to $3,150 for the purchase of a Prius in 2006-2007. At the state and local level, incentives for hybrid vehicle adoption have included income tax credits, sales tax exemptions, reduced parking fees, exemption from emissions testing and permission to use high occupancy vehicle (HOV) lanes with only a single occupant (see Appendix B for details).
The history of the Prius in the United States provides a compelling example of diffusion under supply constraint, exhibiting both waiting lists during times of excess demand and discounting at times of surplus inventory. Various studies have used econometric approaches to reveal the determinants of Prius adoption (see Diamond (2009), Sallee (2007) and Sims Gallagher and Muehlegger (2008)), including estimation of the effectiveness of different government incentive designs. However, these studies do not consider the effect of dealer incentives (either explicitly or because dealer incentives weren't offered during the dates studied) on consumer adoption. Sallee identifies the presence and importance of wait lists, but treats them with a dummy variable, explaining neither the origins nor length of wait lists observed. In the following section, a model of new product diffusion is developed that incorporates wait lists and price dynamics in the presence of supply constraints.

4. Model Formulation

The model of diffusion with supply constraints and price feedback that I develop here builds on the foundations of Bass-type diffusion models, with several extensions. The family of Bass models confounds the effects of social exposure, accumulated familiarity, decision variables (such as purchase price and operating cost) and supply constraints. Durable goods are often expensive and possess multiple performance attributes, requiring consumer learning through social exposure prior to decision to adopt. To understand the complex diffusion dynamics of durable goods in the presence of supply constraints, explicit delineation of the multiple causal mechanisms influencing consumers' decision to adopt is needed. The model described here combines key three elements: 1) consumer choice between discrete alternatives using a logit decision model (McFadden 1980); 2) the accumulation of consumer familiarity from marketing and word-of-mouth, drawing heavily on the familiarity model developed by Struben and Sterman (2008); and 3) the new product supply chain. The model is formulated as a system of non-linear differential equations in continuous time. As an analytical solution is not known, simulation is used to solve for the dynamics.
4.1 Consumer Choice

Consumers make a choice about the technology they will purchase based on the attributes of the available alternatives. Consumers are assumed to choose between the new technology and comparable conventional alternatives. The share of consumers currently using technology $i$ who adopt technology $j$ is given by:

$$\sigma_{i,j} = \frac{e^{u_{i,j}^o}}{\sum_j e^{u_{i,j}^o}} \tag{1}$$

where $u_{i,j}^o$ is the expected utility of technology $j$ as perceived by drivers of technology $i$. The expected utility of a technology depends on both the utility of that technology and the extent to which a customer is familiar with that technology such that they are willing to include that technology in their consideration set for the purchase decision:

$$u_{i,j}^o = u_{i,j} \times F_{i,j} \tag{2}$$
where $F_{ij}$ is the level of familiarity users of technology $i$ have with technology $j$. 'Familiarity' captures 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 and Sterman 2008). Consumers' familiarity with the each platform is influenced by social and cognitive processes; increasing with exposure to marketing and word-of-mouth, and decaying through forgetting:

\[
\frac{dF_{ij}}{dt} = z_{ij} (1 - F_{ij}) - \phi_{ij} F_{ij}
\]

where $z_{ij}$ is the total effect that social exposure has on familiarity with technology $j$ and $\phi_{ij}$ is the fractional rate at which familiarity is lost. Unless consumers pay attention to new technologies and trends, their familiarity with those new technologies erodes with time. Generically, this familiarity loss function takes the following form, with the rate familiarity loss fastest when the consumer's level of familiarity with technology $j$ is low:

\[
\phi_{ij} = f(F_{ij}) \quad \text{where} \quad \phi_{ij} \geq 0 , \frac{\partial \phi_{ij}}{\partial F_{ij}} < 0 , \frac{\partial^2 \phi_{ij}}{\partial F_{ij}^2} > 0
\]

For durable goods, the dynamics of the installed base of the technology plays an important role in the diffusion process. After consumers make their initial purchase, repeat purchases only occur when the technology ages or breaks, assuming consumers do not own multiple technologies concurrently. The turnover of the installed base over time also plays an important role in the accumulation of consumer familiarity in the population of non-adopters. Those who have already adopted technology $i$ have full familiarity with technology $i$, making them more likely to buy technology $i$ again than non-adopters who have less familiarity, $F_{ij} \leq 1$. A detailed representation of the installed base would capture multiple age cohorts with age-specific hazard rates of replacements, but this detail is not needed to understand the fundamental dynamics. However, a single installed-base stock is insufficient, because new purchases almost always remain in the installed base for a minimum period of time, assuming high build quality of new technologies. Here I use a two-stock model of the installed base, represented by a stock of Newer Adoptions of each technology $i$, $Q_i$, and a stock of Older Adoptions of technology $i$, $U_i$. The stock of Newer Adoptions is given by Dealer Sales less Newer Adoption Aging and Newer Adoption Retirements:
where $\omega$ is the fraction of Newer Adoptions retired prematurely each month due to breakage, and $\tau_a$ is the technology aging time constant. The stock of Older Adoptions is given by Newer Adoption Aging less Older Adoption Retirements:

$$
\frac{dQ_i}{dt} = s_i - \omega Q_i - \frac{Q_i}{\tau_a}
$$

(5)

where $\tau_r$ is the average time at which older adoptions are retired. The fraction of buyers who are currently adopters of technology $i$, $\varphi_i$, is given by the fraction of Newer Adoptions of technology $i$, and the fraction of Older Adoptions of technology $i$, weighted by $K$, the fraction of sales that come Newer Adoptions:

$$
\varphi_i = K \sum_{V_i} \frac{Q_i}{\sum_{V_i}} + (1-K) \frac{U_i}{\sum U_i}
$$

(7)

Social exposure to technology $j$ is the sum of four factors: (i) the socialization effect of marketing, $z_{m,j}$ (ii) the socialization effect of word-of-mouth from adopters of technology $j$, $z_j$ (iii) the socialization effect of consumers who haven't adopted technology $j$, $z_{kj}$ and (iv) the socialization effect of word-of-mouth from consumers waitlisted by adopt technology $j$, $z_{w,j}$:

$$
Z_{i,j} = z_{m,j} + z_j + z_{w,j} + \sum_{V_k=j} z_{k,j}
$$

(8)

The socialization effect of marketing is equal to the level of marketing spending on technology $j$, $c_{m,j}$, multiplied by the coefficient of marketing effectiveness, $e_m$: 

22
\[ z_{m,j} = e_{m} \cdot c_{m,j} \]  

The socialization effect of word-of-mouth from each consumer group is calculated as the effective contact rate from each group, multiplied by the fractional installed base of that group. The effective contact rate is the net rate at which contact between two individuals results in the generation of familiarity from one to the other, the product of the number of contacts the individual of interest makes with others each month with the probability that each contact results in the transfer of familiarity from one to the other. For example:

\[ z_{j} = e_{j} \cdot \left( \frac{N_{j}}{N} \right) \]  

4.2 Dealer Inventory Management and the Customer Wait List

The number of units of technology \( j \) in dealer inventories, \( I_{j} \), increases with deliveries of inventory to dealers, \( x_{j} \), and decreases with units sold to customers, \( s_{j} \):

\[ \frac{dI_{j}}{dt} = x_{j} - s_{j} \]  

Sales are the lesser of the maximum shipping rate possible given the inventory on hand and the desired shipping rate given the number of customers on the wait list:

\[ s_{j} = \min \left( \frac{I_{j}}{\tau_{j}}, \frac{W_{j}}{\tau_{w}} \right) \]  

where \( \tau_{j} \) is the average time needed to prepare a unit of technology \( j \) from the dealership inventory for customer handover, and \( \tau_{w} \) is the average time needed for a customer to be recalled from the waitlist and visit their dealership to complete their purchase transaction. The wait list for technology \( j \), \( W_{j} \), increases with customer demand for technology \( j \), and decreases with sales of technology \( j \) and with customers reneging from the wait list:
\[
\frac{dW_j}{dt} = d_j - s_j - r_j
\]  

(13)

where the rate of reneging is given by the fraction of the wait list reneging each month, \( f_r \), as those customers choose to buy an alternative technology or no technology at all:

\[ r_j = W_j \cdot f_r \]  

(14)

Given non-trivial inventory holding costs, dealers manage their inventory using incentives, estimating their inventory coverage based on their sales forecast. Initially, a lack of historic sales prevents the dealers from basing their sales forecast on recent customer orders, so they must rely in part on the demand forecast provided to them by the manufacturer's marketing department, \( \hat{s}_j^m \).

Thus, the sales forecast, \( \hat{s}_j \), is developed from these two sources of information:

\[ \hat{s}_j = \delta \cdot \hat{s}_j^d + (1 - \delta) \cdot \hat{s}_j^m \]  

(15)

where \( \delta \) is the weight the dealer attaches to their own forecast relative to the manufacturer's marketing forecast, estimated as the cumulative number of sales of technology \( j \), \( S_j \), relative to a decision-making experience threshold, \( S_j^* \):

\[ \delta = \max \left( \frac{S_j}{S_j^*} \right) \]  

(16)

The dealers' expected inventory coverage is the current level of inventory divided by their current sales forecast:

\[ c_j = \frac{I_j}{\hat{s}_j} \]  

(17)
The dealers' forecast of monthly sales of technology $j$, $\hat{s}_j^d$, is assumed to be a moving average of past sales, using an Erlang lag (3rd order). Dealers assess the size of the incentive they should offer to consumers, $v_j^d$, if any, based on their level of inventory coverage. Generically, this incentive takes the functional form:

$$v_j^d = f(c_j) \quad \text{where}: \quad v_j^d \geq 0, \quad \frac{\partial v_j^d}{\partial c_j} > 0, \quad \frac{\partial^2 v_j^d}{\partial c_j^2} << 0$$ (18)

5. Model Estimation

To estimate model parameters for the case of the Prius, I make a number of elaborations to the generic model described above. I reduce the complexity of the numerous makes, models and body styles in the automotive market, assuming here that consumers choose between the Prius and a comparable gasoline vehicle within an individual market segment. For the first generation Prius (2000-2003), a compact car, I assume the comparable vehicle is the Toyota Corolla. For the second (2004-2009) and third (2010-current) generation Prius, mid-size cars, I assume the comparable vehicle is the Toyota Matrix. Given the long-standing dominance of the conventional gasoline/internal combustion regime, I assume that all drivers are fully familiar with the conventional gasoline technology, so $F_{i,p} = 1$. When first introduced, all drivers are completely unfamiliar with the Prius, so $F_{i,p} = 0$, resulting in an initial market share of zero. The utility of the Prius and conventional gasoline technologies is estimated based on four observed attributes: purchase price, operating cost, range and greenhouse gas emissions. Weights for these attributes are obtained from the revealed-preference multinomial logit model of alternative fuel vehicle preferences estimated by Brownstone, Bunch et al. (2000). The effective purchase price paid by the customer is the Manufacturer’s Suggested Retail Price (MSRP) less incentives offered by federal, state and local governments, $v_j^f$, $v_j^i$, and $v_j^d$ respectively, as well as the discount offered by the dealer, $v_j^d$.

---

1 I attempted unsuccessfully to estimate the full model including both socialization and consumer utility coefficients. These estimation issues are described in Appendix C.
The relationship between the level of dealer inventory coverage and the Prius incentive offered was derived analytically from transaction data collected by Power Information Network (J.D. Power and Associates 2010) as a standard power-law function:

\[ p_j^d = p_j^{MSRP} - v_j^d - v_j^s - v_j - v_j^f \]

\[ v_j^d = \max \left( 0, 3000 - 7256 \left( c_j \right)^{-0.69} \right) \]

Finally, production of the Prius is exogenously specified based on actual Prius exports from Japan (where all Prius vehicles are manufactured) to the United States. A full description of the data sources used is available in Appendix A.

6. Results

The socialization parameters that best explain the observed diffusion of the Toyota Prius in the US were estimated using non-linear least squares regression. Socialization parameters for four alternative models are shown in Table 1: the classic Bass model of innovation diffusion, the Familiarity model developed by Struben and Sterman (2008) and two variants of the Supply Constraints model described in this paper. Due to the nonlinearities in the model and serial correlation in the residuals, confidence intervals were estimated by bootstrapping (Dogan 2007). The details of the bootstrapping method are described in Appendix B.
Table 1: Estimation of Socialization Parameters for the Diffusion of the Toyota Prius

<table>
<thead>
<tr>
<th>Socialization Parameter</th>
<th>Bass Model</th>
<th>Familiarity Model</th>
<th>Supply Constraints Model</th>
<th>Supply Constraints Model + Socialization from Waitlist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient of Innovation (p)</td>
<td>5.2E-05***</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(1.5E-05, 0.0001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficient of Imitation (q)</td>
<td>0.0173*</td>
<td>0.0004***</td>
<td>0.0006***</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(-7.1E-06, 0.034)</td>
<td>(0.0002, 0.0005)</td>
<td>(0.0005, 0.0007)</td>
<td>(-0.0001, 0.0017)</td>
</tr>
<tr>
<td>Marketing Effectiveness</td>
<td>-</td>
<td>-</td>
<td>0.5140***</td>
<td>0.3261***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.0800, 1.0822)</td>
<td>(0.1515, 0.5845)</td>
</tr>
<tr>
<td>Effective Contact Rate – Prius Drivers</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>7.22E-05</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>(-0.0005, 0.0005)</td>
</tr>
</tbody>
</table>

(lower, upper) = 95% confidence interval. *** = significant at $p = 0.01$. ** = significant at $p = 0.05$. * = significant at $p = 0.1$.

Table 2: Goodness of Fit Statistics - Prius Supply Constraints Model

<table>
<thead>
<tr>
<th>Socialization Parameter</th>
<th>Bass Model</th>
<th>Familiarity Model</th>
<th>Supply Constraints Model</th>
<th>Supply Constraints Model + Socialization from Waitlist</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² – Sales</td>
<td>0.4477</td>
<td>0.5815</td>
<td>0.8104</td>
<td>0.8055</td>
</tr>
<tr>
<td>R² – Waiting List</td>
<td>-</td>
<td>-</td>
<td>0.3040</td>
<td>0.2710</td>
</tr>
<tr>
<td>R² – Dealer Incentive</td>
<td>-</td>
<td>-</td>
<td>0.0539</td>
<td>0.0565</td>
</tr>
<tr>
<td>MAPE – Sales</td>
<td>0.3336</td>
<td>0.3321</td>
<td>0.2755</td>
<td>0.2793</td>
</tr>
<tr>
<td>MAPE – Waiting List</td>
<td>-</td>
<td>-</td>
<td>0.9853</td>
<td>1.009</td>
</tr>
<tr>
<td>MAPE – Dealer Incentive</td>
<td>-</td>
<td>-</td>
<td>0.1725</td>
<td>0.1723</td>
</tr>
<tr>
<td>Theil Bias Fraction (U=) – Sales</td>
<td>0.0052</td>
<td>0.0400</td>
<td>0.0055</td>
<td>0.0087</td>
</tr>
<tr>
<td>Theil Unequal Variance Fraction (U) – Sales</td>
<td>0.1739</td>
<td>0.0132</td>
<td>0.0015</td>
<td>0.0009</td>
</tr>
<tr>
<td>Theil Unequal Covariance Fraction (U²) – Sales</td>
<td>0.8209</td>
<td>0.9468</td>
<td>0.9930</td>
<td>0.9905</td>
</tr>
</tbody>
</table>

Estimates for the Bass diffusion model, a foundation of the innovation diffusion literature, is presented here as a baseline. The Bass model identifies two classes of adopters: innovators, who choose to adopt of their own accord, and imitators, whose adoption decision is influenced by the installed base of adopters. Hence, the Bass model is a generalization of the most fundamental diffusion dynamics that generate the stylized S-shaped adoption curve. The estimated values of $p$ and $q$ are consistent with the literature applying the Bass model to other consumer durables. The coefficient of innovation, $p$, is commonly less than 0.01 for annual data, while the coefficient of imitation, $q$, is commonly between 0.3 and 0.5 for annual data (Mahajan, Muller et al. 1995). Once
annualized ($p = 0.0006$ and $q = 0.2076$), the Bass parameters for the case of the Prius are at the low end of these ranges, which may be explained by the price disadvantage faced by hybrid vehicles relative to the conventional gasoline alternative and the slow rate of turnover of the US vehicle fleet.

The Familiarity model developed by Struben (2006) extends the Bass model, explicitly recognizing the difference between factors that influence the attractiveness (or utility) of an innovation for consumers from factors that influence the awareness (or familiarity) consumers have with that innovation. In the Prius case, this distinction allows the Familiarity model to control for influences such as purchase price, operating cost and government incentives. Using only two socialization parameters, conceptually equivalent to the Bass model, the Familiarity model is able to capture substantially more of the variation in Prius sales than the Bass model. As with the Bass model, the Familiarity model highlights the role of marketing and social contagion in the diffusion of the Prius. Toyota’s spending on print, television, Internet and outdoor advertising for the Prius over the decade since 2000, totaling an estimated $280 million, has been an important source of consumer information about the Prius. The other source of information found to be significant is ‘word-of-mouth’, the effect that the installed base of Prius adopters has on the adoption decision of potential adopters. The word-of-mouth parameter estimated in this model captures communications that occur through multiple channels, including: interpersonal discussions, observation of Prius vehicles in use, and media attention paid to the Prius, in articles such as car reviews.

The Supply Constraints model developed here further extends the Familiarity Model, incorporating the role that production capacity and dealer inventories have on the diffusion process. The importance of capturing supply constraints in diffusion models is highlighted when the results of this model are compared with the familiarity model that only captures the demand-side dynamics. The Familiarity model provides a worse fit to the historical sales trend, and lacks entirely the ability to replicate observed trends in waiting lists and discounting, because the model does not consider the role of product availability and dealer inventories in the diffusion process. More importantly, the Familiarity model systematically biases diffusion parameter estimates when supply constraints have a significant influence on the diffusion process, demonstrating empirically a theoretical result first proposed by Ho, Savin et al. (2002). In the uncapacitated Familiarity model, unsatisfied customer demand captured by Prius waiting lists is ignored, under-estimating the aggregate level of demand. The bias is reflected in the difference between the socialization
parameter estimates revealed by the Familiarity and Supply Constraints models respectively. These parameter estimates are statistically different from zero at $p = 0.01$ in each case.

Earlier I proposed that word-of-mouth about the Prius may also be generated by non-Prius drivers, to the extent that they possess some familiarity with the Prius due to their exposure to marketing and their own interactions within their social networks. Despite the intuitive existence of this effect, estimating the socialization that occurs from non-Prius drivers using regression is not possible in this application (If the number of non-Prius drivers $N_{np} = N_t - N_p$, the total number of drivers $N_t$ is large and constant, and the number of Prius drivers $N_p$ grows slowly, $N_{np}$ and $N_p$ are essentially perfectly correlated).

Simulation of the calibrated Supply Constraints model demonstrates that this model is able to closely replicate the historic Sales trend, shown in Figure 8. The result is not surprising, given that production supply constraints limit the potential for sales growth, while the balancing price feedback in the model captures dealer efforts to generate sales when excess inventory is on hand. The model captures the overall trend of waiting list and dealer incentive data but with less accuracy, shown in Figure 9 and Figure 10, which is not surprising giving the measurement noise that exists in these datasets. From January 2009, noticeable divergence exists between the waiting list data and the waiting list simulated by the model, with the model overestimating demand for the Prius. This may be explained by the Prius came under increasing competition within the hybrid vehicle sector in 2009, with increasing sales of the Toyota Camry hybrid and the re-introduction of Honda's Insight hybrid in March 2009, a direct competitor to the Prius, offerings not capturing in the model's binomial choice structure. This model does not explicitly capture consumers' decisions to delay their vehicle purchase immediately prior to the introduction of a new model generation, as occurred for the Prius in 2003 and 2009. Also, this model does not capture the considerable negative publicity the Prius received in early 2010 due to safety recalls for problems with the Prius' anti-lock braking system.

Earlier, I speculated about the effect that the Prius waiting list itself might have played in the consumer socialization process. Adding the length of the waiting list as a regressor in the Supply Constraints model provides a marginal improvement in overall fit (despite a marginal reduction in fit to the Sales data as shown in Table 2), and reveals a positive coefficient on the length of the waiting list. This result suggests that the existence of a waiting list had a positive effect on consumer demand, presumably due to the media attention paid to the waiting lists and the word of mouth generated by Prius buyers on the list. However, including the influence of the waiting list reduces the statistical significance of the other socialization parameters. The model
suggests that the strength of socialization from the wait list increased with the length of the wait list, although my finding is not globally robust. Eventually, the length of the wait list will frustrate potential adopters, having a negative effect on the diffusion process suggesting that the influence takes an inverted-U shape. My efforts to estimate the relationship empirically were unsuccessful, possibly due to the relatively small number of wait list data points, and the existence of considerable measurement noise in the observed wait list length data.

**Figure 9: Comparison of Simulated and Actual Sales**

![Graph comparing actual and simulated sales of US Prius over time](image)
Figure 10: Comparison of Simulated and Actual Wait List Lengths

Figure 11: Comparison of Simulated and Actual Average Dealer Incentive Offered
Figure 12: Consumer Familiarity with the Prius (All Light Vehicle Drivers)

Figure 13: Effect of Supply Constraints on Model Performance
Figure 14: Familiarity Models with Full Familiarity and Constant Utility

The simulated accumulation of gasoline drivers' familiarity with the Prius over the period 2000-2010 is shown in Figure 10. Familiarity with the Prius as quantified by this model has grown over that time, with a considerable step in 2009 resulting from a spike in Toyota's Prius marketing effort, as shown in Figure 4. These results suggest that familiarity with the Prius (and by extension hybrid vehicles in general) remains relatively low, with the potential for considerable further market penetration as consumer familiarity continues to develop. This finding is consistent with a recent survey that sought to understand that extent of consumers' awareness of alternative fuel vehicle technologies. Of 1,207 US drivers surveyed, only 22% considered themselves 'very familiar' with gasoline hybrid-electric vehicles, up from 15% in 2006 (Maritz Research 2011). These stated preferences may be biased high also, because merely being knowledgeable about these technologies does not mean the respondents have accepted the technology into their consideration set, and respondents may shape their answers to appear knowledgeable.

Finally, as this model combines a behaviorally oriented diffusion structure with a utility-oriented discrete choice structure, it is interesting to consider the contribution that each of these approaches makes to explain the variation observed in the data. Two additional models were developed to explore this question, building on the demand side-only Familiarity model, so as to isolate these dynamics from the impact of the supply constraints and price feedbacks captured in
the full model. In the 'Constant Familiarity' model, the Familiarity model was altered such that all the variation in simulation is driven the discrete choice structure, with only the free parameter being the constant level of familiarity that gasoline vehicle drivers have with the Prius. In the 'Constant Utility' model, the Familiarity model was altered so that each element of the discrete choice structure (including MSRP, government incentives, operating cost, household income, vehicle range and greenhouse gas emissions) takes its average value from the data, such that it estimates a constant market share for the Prius within a constant-sized market segment. In this model, all the variation observed in the simulation is driven by the word-of-mouth and marketing elements of the familiarity structure. Calibrating each of these models to the historic sales data, shown in Figure 13, highlights the distinct contribution each of these elements makes to adoption. The Constant Utility model effectively explains the underlying growth in Prius adoption, responding to both the growing installed base of Prius vehicles and Toyota's marketing efforts, but fails to capture the short-term fluctuations in sales in response to factors such as gasoline prices, government incentives and dealer incentives. In contrast, the Constant Familiarity model captures much of the short-term variation in sales, but overstates sales in early years and understates sales in later years, because this model does not adequately explain how consumers come to learn about and accept this innovation.

7. Policy Analysis

New product launch involves numerous strategic decisions for manufacturers such as Toyota, such as how best to price their product, market it to consumers and distribute the available inventory to different geographic markets, based on future expectations about consumer demand, production costs, the potential to expand production capacity. Here I consider one particular strategy question: What is the optimal mix of vehicle pricing and marketing spending that maximizes Toyota's profits from the Prius platform? This question is of particular interest, because it informs our understanding of the extent to which Toyota's incentives are aligned with the socially optimal product launch strategy, which intuitively would be to produce as many Prius vehicles as possible, and sell them as cheaply as possible.

To address this research question, I find the pricing and marketing spending policies that maximize Toyota's profits, assuming exogenous production capacity. I calculate cumulative profits earned by Toyota and its dealerships, \( \pi \), as revenue \( R \) less costs \( C \):
\[
\pi = R - C \\
\pi = \sum_{i=0}^{T} \left[ s_p \left( P_p - c_p - c_d \right) - c_m \right]
\]

where \( s_p \) is the monthly rate of Prius sales, \( P \) is the transaction price, \( c_p \) is the unit cost of Prius manufacturing, \( c_d \) is the dealer cost of selling each Prius and \( c_m \) is Toyota's marketing spending on the Prius. I do not partition profits between Toyota and its dealership network, because data describing transaction pricing. Detailed estimation of this profit function would require knowledge of the short-run and long-run cost curves of Toyota and its suppliers to manufacture each additional Prius, as well as knowledge of the transaction pricing that occurs between Toyota and its dealerships, and the commissions paid to dealer salespeople. In the absence of this proprietary manufacturing cost data, I estimate the unit cost of Prius manufacturing from the published Dealer Invoice price, \( \delta_p \):

\[
c_p = \frac{\delta_p}{1 + m_p}
\]

where \( m_p \) is the markup over the unit cost of manufacturing. Here I assume that the markup rises linearly from -5% in year 2000 to +5% in year 2009, based on anecdotal evidence that Toyota lost money on each Prius sold initially (Ohnsman 2001; Newsweek 2008), generating an estimate of the cost of manufacturing the Prius over time (Figure 15). Here the estimated Prius manufacturing cost falls over time, consist with expectations regarding learning and economies of scale, with step increases in later years when second and third generation Prius vehicles were larger and included more content.
I estimate $c_d$ as the 25% commission commonly paid to new car salespeople (WardsAuto 2000):

$$c_d = 0.25(P_p - c_p)$$  \hspace{1cm} (23)

With endogenous production capacity, shipments of Prius vehicles to dealers depend on the level of utilization of the available production capacity:

$$x_p = Z_p \cdot \theta_p$$  \hspace{1cm} (24)

where $Z_p$ is the available Prius production capacity and $\theta_p$ is the level of production capacity utilization. The available production capacity is assumed to be an exponential smoothing of the desired production capacity, $Z^*_p$. The extent to which the available production capacity is utilized is a function of the desired level of production relative to the current production capacity. Because changes to the physical production capacity are expensive and time consuming, changes to production in the short-term can be achieved by working harder or adding or laying off production
shifts. Capacity utilization is a function of schedule pressure, $\rho_p$, where schedule pressure is the ratio of desired production capacity to available production capacity. Generically, capacity utilization takes the following form:

$$\vartheta_p = f(\rho_p) \quad \text{where} \quad \vartheta_p \geq 0, \quad \frac{\partial \vartheta_p}{\partial \rho_p} \geq 0, \quad \frac{\partial^2 \vartheta_p}{\partial \rho_p^2} < 0$$

(25)

The desired level of production capacity, $Z^*_p$, is based on the current dealer sales forecast, adjusting for the level of inventory available and the number of customers on the waitlist:

$$Z^*_p = \hat{s}^*_p + \frac{I_p}{\tau_{AL}} + \frac{W_p}{\tau_{AW}}$$

(26)

where $\tau_{AL}$ is the time to adjust desired production due to the level of inventory, and $\tau_{AW}$ is the time to adjust desired production due to the length of the waitlist. Calibration of this endogenous production feedback loop to Toyota’s Prius production schedule over the period 2000-2009 reveals that in the case of the Prius: $\tau_{AL} = 16.5$ months, $\tau_{AW} = 7.6$ months and $\tau_{AW} = 15.5$ months. With these assumptions, the profit maximizing strategy for Toyota would have been to mark up the Prius by 74%, much more than was observed, and use the additional revenue to drastically increase marketing spending by 7800%. While these policy prescriptions are aggressive, and should be interpreted in the context of a simplified model, which has no capacity adjustment costs and constant returns on marketing effort, the optimal policies are instructive directionally. Toyota might have increased its profits by charging more for the Prius, and using the proceeds to spend more on Prius marketing, accelerating the accumulation of consumer familiarity that would have generated sufficient demand for the Prius at the higher price. I compare these findings with the intuitive policy that would maximize Prius adoption, and, by extension, minimize fuel consumption and greenhouse gas emissions: make as many Prius vehicles as possible, price them as cheaply as possible, and spend as much as possible on marketing to building consumer familiarity. The profit-maximizing policy is in conflict with the adoption-maximizing policy, reinforcing the ‘profits or the planet’ mindset embedded in frameworks such as triple bottom line reporting, and informs why Toyota may have pursued a conservative production schedule. Insufficient capacity in the manufacturing supply chain may have prevented Toyota from making more Prius vehicles,
regardless of the level of demand, and the market prospects for this new product category were highly uncertain in 2000 when the Prius was released. However, pursuing a cautious production schedule also improves the probability that demand will exceed the available supply, maintaining high transaction prices that generate revenue for marketing spending. The limitations of this policy analysis highlight opportunities for future research. Refining this analysis will require detailed data such as the short-run and long-run Prius supply curves, the production learning curve achieved in hybrid powertrain components and the transfer pricing that occurs between Toyota and its dealers.

8. Discussion

This paper adds to the literature on innovation diffusion under supply constraints and also informs how our understanding of how consumer adoption of durable technologies such as hybrid-electric vehicles may evolve over time. I establish the relationship between supply constraints, waiting lists and prices: When persistent consumer demand exceeds the available supply of the product, and the firm is unwilling to raise the price of that product, potential adopters join the waiting list for that product, causing sales to be delayed or foregone. When supply constraints in production lead to the accumulation of surplus inventory, retailers manage this inventory by discounting the product to stimulate sales. Applying this model to the case of the diffusion of the Toyota Prius hybrid-electric vehicle in the United States, I demonstrate that this model is able to effectively replicate observed trends in Prius sales, waiting lists and dealer incentives. Interestingly, the existence of waiting lists may not be as detrimental as suggested by the classical queuing literature, if the waiting list is beneficial to the extent that it builds further consumer familiarity with the new product through positive word-of-mouth. In the opposite case, where surplus inventory exists, the act of discounting works to ensure that all inventory does get sold, although at a price less that the MSRP. The estimation results are consistent with the theoretical finding of Ho, Savin et al. (2002), who showed that the failure to capture supply constraints in diffusion models and forecasts may result in systematic bias in the estimation of diffusion model parameters. When waiting lists exist, parameter estimation based on actual sales will underestimate the level of demand that exists for a product, because unsatisfied demand exists that isn't reflected in actual sales data. For practitioners, this paper helps practitioners understand how forecasting errors affect both the price received for the product as well as future demand for that product in light of the inherent uncertainty that exists when forecasting future demand.

Given the existence of persistent Prius waiting lists, it is interesting to consider why Toyota did not act more aggressively to alleviate waiting lists by increasing Prius production. It has been
suggested that Toyota was selling the Prius at or below the cost of production initially (Mufson 2008). This aggressive strategy may be considered rational given Toyota's overwhelming market leadership, allowing learning and economies of scale to be privately appropriated without a competitive response from rivals (Spence 1981; Fudenberg and Tirole 1983). By erring on the side of insufficient production relative to consumer demand, Toyota was able to maintain high prices for the Prius, minimizing losses, while benefiting from the hype surrounding Prius waiting lists. While Toyota did not raise the MSRP of the Prius in response to surplus demand, anecdotal evidence provides insights into how individual Toyota dealerships sought to maximize profits when waiting lists existed for the Prius. First, some dealers engaged in price 'gouging', raising prices above Toyota's MSRP, a practice criticized by Prius enthusiasts (GreenHybrid 2004). Second, more subtly, some dealers stocked mostly high trim-level Prius models when waiting lists existed, boosting dealer profits due to the higher margin possible on these vehicles when sold at or near MSRP. By raising consumers' reference price for the Prius, dealers in the second example were able to largely avoid the transaction disutility (perception of price gouging) consumers felt in the first example. Further analysis of the sales mix of Prius models over time would shed light on the extent to which this practice existed.

The Prius case reveals important insights for the design of public policy instruments intended to accelerate adoption of clean energy technologies. If the rate of adoption of the new technology is governed by the availability of supply, not the level of consumer demand, the introduction of incentives cannot stimulate any further adoption. When the Federal Government introduced the $3,150 tax credit for the purchase of a hybrid vehicle in January 2006, a waiting list of approximately 2 months existed to purchase a new Toyota Prius. By April 2006, the waiting list had grown to an estimated 4.5 months. These conditions indicate that the same rate of Prius adoption, the dominant model available in the hybrid vehicle market, could have been achieved with a lesser incentive, or no additional incentive at all. At the same time, freeriding on that incentive existed, because Prius sales completed at that time were sold at a price less than the price that would have cleared the market. Similar dynamics have been reported in other clean technology markets, such as the market for solar photovoltaic panels in Spain (BBC News 2007). These mismatches may have been as much the result of deliberative and legislative delays in the development of the policies, as much as flawed policy design. However, these examples demonstrate the need for careful coordination between the designers of policy instruments and the producers of new technologies, and the potential for dynamic inefficiencies if the levels of incentives are set in legislation directly.
This research highlights factors governing the diffusion of HEV technology into the US light vehicle fleet, and also the role of HEV technology in the fleet looking forward. First, improving the effectiveness of the hybrid powertrain and reducing its incremental cost over conventional gasoline vehicles will obviously provide a more compelling value proposition for consumers. How might this be achieved? The continued proliferation of vehicle models with hybrid powertrains will provide consumers in all market segments the opportunity to purchase a hybrid vehicle. While over 30 hybrid vehicle models are available in the United States at present, a number of markets still lack sufficient hybrid offerings, such as the compact car, wagon and sports car segments. In addition to 'full' HEVs (which can drive in 100% electric mode in limited circumstances), the development of more 'mild' HEV options such as the Buick Lacrosse with eAssist that have more limited functionality (and less fuel savings) but a lesser incremental cost will allow more car buyers access to hybrid vehicles choices also. Proliferation of models has the additional benefit of helping the industry to achieve economies of scale and drive technology costs down the learning curve. For models where a hybrid powertrain is an optional extra such as the Toyota Camry, unbundling the hybrid option from other options such as power windows and navigation systems will help provide consumers access to HEVs at the least incremental cost.

Investing in efforts to improve consumer familiarity with hybrid vehicles should result in growth in consumer demand and reach consumers who might not otherwise seek out information about HEVs. The deployment of hybrid taxis is an important opportunity that has been employed by some cities, using policy instruments such as discounted medallion prices (as used in New York City), preferential 'front of the line' treatment at airports (as used at Boston Logan airport), or direct financial incentives to medallion owners for hybrid vehicle purchases (as using in San Francisco). Preferential pricing has been used by car sharing services such as Zipcar and the 'uber' hire car service, recognizing the reduced operating costs of HEVs. Incentives aimed at hire car companies could be similarly successfully, aligning the consumer's economic incentive with the opportunity to experience an HEV firsthand. At car dealerships, extended test-drive opportunities that provide consumers sufficient time to learn about the attributes of HEVs are important, because observations such as the rate of which fuel is being consumed from the tank are unlikely to be made during a 'lap around the block'.

More generally, rising gasoline prices provide greater economic incentive for consumers to invest in vehicle fuel economy (just as falling gasoline prices reduce this incentive). Policy mechanisms that provide this incentive include raising the gas tax, or instituting a price on carbon, which both increase the economic benefit of using gasoline efficiently. However, an open question
is the role that HEVs play in the light vehicle fleet looking forward. HEVs seem to have a critical role in achieving greenhouse gas emissions reduction targets in the short to medium term, with significant barriers facing leading alternative fuel candidates such as electric and hydrogen vehicles at present. However, HEVs are still dependent on gasoline, and cannot achieve deep reductions in greenhouse gas emissions in the long run (such as 80% below 1990 or 2000 levels by 2050). To do so, the will still need to transition to alternative fuels at some point in the future, which may not be made easier if the success of fuel-efficient HEVs has lowered vehicle operating costs, providing less economic incentive to invest in AFVs.

9. Future Research Opportunities

The model developed here reveals numerous opportunities for future research. This case study demonstrates that the failure to capture supply constraints in diffusion models can result in systematic bias in diffusion parameter estimates, consistent with prior theory, but not previously demonstrated empirically. This result encourages further empirical analysis where waiting lists and discounting have been observed, such as markets for mobile electronic devices, video game consoles and children’s toys. Given the demonstrated significance of supply constraints in new product diffusion, further opportunities exist to understand the interactions between supply constraints and factors considered in the diffusion literature previously, such as multiple product generations, and diffusion of products through time and space. Third, this model provides a valuable foundation for further analysis of markets for hybrid and electric vehicles. A highly simplified representation of the vehicle fleet is used here, aggregating different vehicle users (individuals, taxis, corporate fleets etc.) and geographic regions across the US into a single driver population. The representation of consumer choice in this model is similarly simplified, with consumers choosing between only the Prius and a single aggregate vehicle representing comparable gasoline vehicles within a single market sector. Extending this analysis to the entire market for hybrid vehicles will provide insights about how word-of-mouth and consumer familiarity spillovers occur across market segments and regional markets.
References


GreenHybrid (2004). "Prius MVA (Price Gouging)."


Appendix A: Data Sources

A.1 Sales

Monthly sales data for the Prius in the United States, along with total monthly light vehicle sales and total monthly car sales, were obtained from the Automotive News Data Center. Annual market shares by EPA Vehicle Class were obtained from Appendix F of the US EPA's report *Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2009* (EPA 2009).

A.2 Government Incentives

Data describing government incentives for which the Prius is eligible were collated from numerous sources, based on the Union of Concerned Scientists' list of hybrid vehicle incentives (UCS 2010). The Federal Government's tax credit for advanced vehicles provided a tax credit of up to $3,150 for the purchase of a Prius in 2006-2007, up to a limit of 60,000 vehicle incentives per manufacturer. The details of state and local government incentives were gathered from numerous government departmental websites. These incentives exist in numerous forms, including tax credits, tax deductions, high-occupancy vehicle (HOV) lane access, exemption from emissions testing and discounted parking. Only financial incentives were included in this model. The value of tax deductions was estimated as 15% of the amount of the tax deduction, the marginal tax rate that has applied to the mean per capita income in the United States each year over the past decade.

A.3 Dealer Incentives

Incentives that influence the price of the Prius include cash rebates to customers, reduced rate financing and discounts to dealers. Weekly data describing the range of incentives being offered by Toyota for purchase of the Prius for the period 2003-2010 were obtained from the Automotive News Data Center. Monthly dealer incentive data was calculated by averaging weekly incentives offered for each month, using a net present value calculation to estimate the present value of reduced-rate financing to consumers. Transaction data obtained from JD Power's Power Information Network, a database of real-time transaction data obtained from across thousands of dealerships in the United States, describes the monthly average incentive offered by Toyota dealers, and the monthly average Prius retention time in dealer inventories.

A.4 Prius Supply
The Prius has been manufactured exclusively in Japan for all global markets since its introduction. Prius export data from Japan to the United States were obtained from Fourin and Toyota. This data was available on an annual basis for 2000-2002, and a monthly basis for 2003-2010. For the period 2000-2004, monthly production and exports were estimated using linear interpolation.

A.5 Marketing Expenditure

Marketing expenditure data for the Prius was obtained from Kantar Media, a marketing intelligence provider. This data measures Toyota's monthly Prius marketing expenditure on radio, television, newspapers, magazines and the internet in the United States.

A.6 Vehicle Specifications

Specifications of the Prius and comparable vehicles such as Toyota's Corolla and Matrix models by Model Year were obtained from a consumer automotive website (CarsDirect 2010), including Manufacturer's Suggested Retail Price ($), Dealer Invoice Price ($), fuel tank capacity (gallons), city and highway fuel economy (miles per gallon) and interior volume (cubic feet). Greenhouse gas emissions (tons of CO2/year) for each vehicle were obtained from the Department of Energy's Fuel Economy website (DOE 2010), based on 12,000 miles of driving per year split between 55% city and 45% highway driving.

A.7 Waiting List Length

The length of the waiting list for new Prius purchase was estimated by analyzing newspaper articles for the period 2000-2010. Articles that referred to a current waiting list for the purchase of a Prius in the US were identified using Factiva. For each month, an estimated waiting list length was calculated as the average of the waitlist estimates mentioned in articles during that month. In addition, the frequency of newspaper references to waiting lists in the US was collated each month. These two data sets, shown in Figure 12, have a correlation of 0.68.

A.8 Gasoline Prices

Monthly average gasoline prices were obtained from the U.S. Energy Information Administration (EIA 2010). The prices used in this analysis were the U.S. city average retail prices for regular automotive gasoline.
A.9 Household Income

National-level household income data was obtained from the U.S. Census Bureau (2010) available on an annual basis for the period 2000-2009. Linear interpolation of this data was used to obtain an estimate of monthly household income.
Appendix B: Government Hybrid Vehicle Incentives

The details of government incentives available across the United States were gathered from numerous sources, building on the Union of Concerned Scientists' list of hybrid vehicle incentives (UCS 2010). Here we summarize the details of these incentives as they apply to the Toyota Prius:

Table 3: Details of Government Incentives

<table>
<thead>
<tr>
<th>Region</th>
<th>Type</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Federal Government Incentives</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>National</td>
<td>Tax Deduction</td>
<td>The Clean Fuel Tax Deduction for Hybrids allowed hybrid buyers to claim a $2,000 one-time tax deduction in 2004 or 2005, limited to new vehicles purchased as far back as 2000 (Department of Energy 2006).</td>
</tr>
<tr>
<td>National</td>
<td>Tax Credit</td>
<td>Hybrid vehicles purchased after December 31, 2005 are eligible for a federal income tax credit of up to $3,400. Credit amounts phase out for a given manufacturer after it has sold 60,000 eligible vehicles (Department of Energy 2012).</td>
</tr>
<tr>
<td><strong>State Government Incentives</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arizona</td>
<td>HOV Lane Access</td>
<td>Beginning February 9th 2007, qualifying low emissions vehicles including the Toyota Prius can drive in any HOV lane in Arizona, regardless of the number of occupants. Scheme capped at 10,000 permits (Katz and Shapiro 1994).</td>
</tr>
<tr>
<td>California</td>
<td>HOV Lane Access</td>
<td>From January 2005, hybrid-electric vehicles that get 45mpg and have SULEV emissions ratings displaying the required decal can access HOV lanes (CARB 2011). Capped at 85,000 vehicles. Rescinded on July 1, 2011.</td>
</tr>
<tr>
<td>Colorado</td>
<td>Tax Credit</td>
<td>From July 1st 2000, Colorado residents are about to claim a tax credit of up to $6,000 for the purchase of a hybrid vehicle. The percentage of the incremental cost covered by the tax credit is determined by the emissions standard met by the vehicle (UCS 2010).</td>
</tr>
<tr>
<td>Colorado</td>
<td>HOV Lane Access</td>
<td>From May 15, 2008, qualifying hybrid vehicles displaying the required decal and transponder can access HOV and HOT lanes. Capped at 2,000 vehicles (Colorado DOT 2011).</td>
</tr>
<tr>
<td>Connecticut</td>
<td>Tax Exemption</td>
<td>Between October 1, 2004 and June 30, 2010, hybrids getting at least 40 mpg are exempt from the state's 6% sales tax (Connecticut DRS 2009).</td>
</tr>
<tr>
<td>Washington, D.C.</td>
<td>Tax Exemption and Reduced Registration Fee</td>
<td>From April 2005, owners of hybrids do not pay excise tax (6-7%) and have a reduced registration fee (DC DMV 2005).</td>
</tr>
<tr>
<td>Florida</td>
<td>HOV Lane Access</td>
<td>A hybrid vehicle certified by the EPA may be driven in a HOV lane at any time if displaying the appropriate decal (FL HSMV 2008).</td>
</tr>
<tr>
<td>Idaho</td>
<td>Exemption from Emissions Testing</td>
<td>From April 1 2008, hybrid vehicles are exempt from the vehicle emission inspection and maintenance program (Idaho VIP 2010).</td>
</tr>
<tr>
<td>Illinois</td>
<td>Rebate</td>
<td>Illinois residents who purchased a hybrid vehicle using a loan from a participating bank or credit unit were eligible for a $1,000 rebate (UCS 2010).</td>
</tr>
<tr>
<td>Louisiana</td>
<td>Tax Credit</td>
<td>From November 2002, a state income tax credit worth 20 percent of the incremental cost of purchasing an OEM AFV was offered, up to a limit of $1,500 (LA DNR 2012).</td>
</tr>
<tr>
<td>Louisiana</td>
<td>Tax Credit</td>
<td>From July 2009, a state income tax credit worth the lesser of 10 percent of the vehicle cost or $3,000 was offered for the purchase of a hybrid vehicle (LA DNR 2012).</td>
</tr>
<tr>
<td>Maine</td>
<td>Tax Credit</td>
<td>Until 2006, Maine provided a sales tax credit of $500 for hybrid cars for which there is no comparable vehicle powered by gasoline, including the Toyota Prius (UCS 2010).</td>
</tr>
<tr>
<td>Maryland</td>
<td>Tax Credit</td>
<td>From July 1 2000 to July 1 2004, the Maryland Clean Energy Incentive Act provided tax credits against the 5 percent vehicle excise tax up to $1,000 for qualifying HEVs from model year 2000 (Maryland State Dept 2000).</td>
</tr>
<tr>
<td>Maryland</td>
<td>Exemption from Emissions Testing</td>
<td>Qualifying hybrid electric vehicles that achieve a city fuel economy rating of at least 50 mpg are exempt from motor vehicle emissions testing and inspection requirements (Maryland MVA 2012).</td>
</tr>
<tr>
<td>Nevada</td>
<td>Exemption from Emissions Testing</td>
<td>From February 2007, hybrid vehicles less than 5 years old are exempt from emissions testing in Clark and Washoe Counties (NV DMV 2012).</td>
</tr>
<tr>
<td>New Jersey</td>
<td>HOV Lane Access</td>
<td>From May 2006, qualifying hybrid vehicles are allowed to travel in the HOV lanes on the New Jersey Turnpike between Interchange 11 in Woodbridge and Interchange 14 in Newark at peak hours (New Jersey DOT 2006).</td>
</tr>
<tr>
<td>New Mexico</td>
<td>Exemption from Excise Tax</td>
<td>From July 2004 to June 2009, hybrid vehicles with an EPA fuel economy rating of at least 27.5 miles per gallon were eligible for a one-time exemption from the motor vehicle excise tax, worth between $600 and $1,000 (New Mexico EMNRD 2012).</td>
</tr>
<tr>
<td>State</td>
<td>Category</td>
<td>Details</td>
</tr>
<tr>
<td>---------------</td>
<td>------------------</td>
<td>---------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>New York</td>
<td>Howard Occupancy</td>
<td>From March 2006, hybrid vehicles with a highway mpg of at least 45 mpg are exempt from occupancy requirements on the Long Island Expressway (New York DOT 2012).</td>
</tr>
<tr>
<td>New York</td>
<td>Tax Credit</td>
<td>Until December 31, 2006, the Alternative Fuel (Clean Fuel) Vehicle Tax Incentive Program provided a tax credit of up to $3,000 for qualifying hybrid vehicles including the Toyota Prius (NSERDA 2012).</td>
</tr>
<tr>
<td>Oregon</td>
<td>Tax Credit</td>
<td>Until the end of 2009, a tax credit of up to $1,500 is available for the purchase of a HEV. Eligible vehicles include the Toyota Prius (UCS 2010).</td>
</tr>
<tr>
<td>South Carolina</td>
<td>Tax Credit</td>
<td>From June 1st 2006, hybrid vehicles are eligible for a state tax credit equal to 20 percent of the federal tax credit scheduled to begin in tax year 2006 (ignoring the phaseout provisions in the federal scheme) (UCS 2010).</td>
</tr>
<tr>
<td>South Carolina</td>
<td>Tax Exemption</td>
<td>From July 1st 2008, a $300 sales tax rebate is provided against the purchase of a hybrid vehicle (UCS 2010).</td>
</tr>
<tr>
<td>Tennessee</td>
<td>Howard Occupancy</td>
<td>From January 1st 2009, hybrid vehicles are authorized for single-occupant use of HOV lanes with an appropriate decal (Tennessee DOT 2012).</td>
</tr>
<tr>
<td>Utah</td>
<td>Howard Occupancy</td>
<td>Until 31st December 2010, vehicles with C plates for clean fuel vehicles are allowed to travel in HOV lanes regardless of the number of occupants (Utah DOT 2011).</td>
</tr>
<tr>
<td>Virginia</td>
<td>Howard Occupancy</td>
<td>From July 2006, hybrid vehicles registers with clean fuel license plates are permitted to use all HOV lanes in Virginia except the HOV-3 requirement on I-95/395 from 6-9am or 3.30-6pm (Virginia DOT 2012).</td>
</tr>
<tr>
<td>Washington</td>
<td>Exemption from Emissions Testing</td>
<td>From June 2002, hybrid vehicles that obtain have an EPA rating of at least 50 mpg city are exempt from emissions control inspections (WA DOL 2012).</td>
</tr>
<tr>
<td>Washington</td>
<td>Tax Exemption</td>
<td>From January 1 2009-January 1 2011, the state sales tax and use tax do not apply to new passenger vehicles that have a hybrid powertrain and have an EPA-estimated highway miles of at least 40 miles per gallon (WA DOR 2011).</td>
</tr>
<tr>
<td>West Virginia</td>
<td>Tax Credit</td>
<td>Until June 2006, an Alternative Motor Vehicle Tax Credit could be claimed for the incremental cost of purchasing a hybrid vehicle, up to a maximum credit of $3,750 for a passenger vehicle (UCS 2010).</td>
</tr>
</tbody>
</table>
Appendix C: Model Calibration and Confidence Interval Estimation

Appendix C describes the methods used to calibrate the models described in this paper to the data collected, and how confidence intervals were estimated on the resulting parameters.

C.1 Calibration Strategy

Due to the non-linear nature of this model, calibration of this model involved the optimization of a payoff function that minimizes the sum of the squares of the residuals between the model and the data (Dogan 2004):

\[-\sum_{t=1}^{T} (w_t \epsilon_t(\theta))^2\]  \hspace{1cm} (27)

where $w_t$ is the weight of the payoff function. When the error terms are independent and identically distributed (IID), following a normal distribution with zero mean, weighting the payoff equal to the standard distribution of the error term will result in parameter estimates that are Maximum Likelihood Estimators (MLE). In each of the models estimated in this paper, the IID assumption did not hold, as described in section B.2. Despite this, the MLE payoff weighting described here was using for this calibration in the absence of a superior approach. For the two variants of the Supply Constraints model, three variables were included in the payoff definition: Prius Sales (vehicles/month), Waiting List Length (vehicles) and Dealer Incentive Offered ($/vehicle). For the Familiarity and Bass models which model diffusion as an exclusively demand-side process, the payoff definition only included Prius Sales (vehicles/month).

The calibration strategy used for this paper was 'full calibration', whereby all available information was included in the payoff function, and all parameters were fit concurrently. The calibration was undertaken on the period January 2003 – December 2009 inclusive, for which all input data was available at monthly intervals (prior to January 2003, Prius export data was only available on an annual basis). As the model is specified in continuous time, a data reporting structure was added to the model to ensure that model variables were appropriately accumulated at monthly intervals for comparison with historic data.

C.2 Parameter Estimation

Numerous studies have analyzed the attributes of consumer choice than influence consumer vehicle purchase decisions, such as vehicle purchase price, operating cost, performance,
greenhouse gas emissions and body style (Brownstone, Bunch et al. 2000; Berry, Levinsohn et al. 2004; Santini and Vyas 2005). However, these studies make standard economic assumptions about rational consumer choice, failing to capture the dynamic accumulation of consumer familiarity with new technologies discussed in this paper. To estimate consumer preferences for vehicle attributes in this model, I first consider the correlation between key variables identified in previous discrete choice and innovation diffusion studies, shown in Table 4:

Table 4: Supply Constraints Model - Regression Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>Cum. Prius Sales</th>
<th>Diff. in Purchase Price</th>
<th>Diff. in Operating Cost</th>
<th>Gasoline Price</th>
<th>Diff. in GHG Emissions</th>
<th>Waitlist Length</th>
<th>Marketing Spending</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Prius Sales</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Purchase Price</td>
<td>-0.63</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Operating Cost</td>
<td>-0.79</td>
<td>0.68</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gasoline Price</td>
<td>0.72</td>
<td>-0.58</td>
<td>-0.97</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in GHG Emissions</td>
<td>-0.75</td>
<td>0.76</td>
<td>0.87</td>
<td>-0.72</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Waitlist Length</td>
<td>-0.37</td>
<td>0.05</td>
<td>0.03</td>
<td>-0.10</td>
<td>-0.12</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Marketing Spending</td>
<td>0.30</td>
<td>-0.30</td>
<td>-0.10</td>
<td>0.04</td>
<td>-0.18</td>
<td>-0.22</td>
<td>1</td>
</tr>
</tbody>
</table>

Several important variables that influence hybrid vehicle attractiveness are highly correlated in my dataset. Cumulative Prius sales, a close proxy for socialization from word-of-mouth, is strongly negatively correlated with vehicle operating cost, because the price of gasoline has risen steadily over the period 2000-2010. Vehicle greenhouse gas emissions is strongly positively correlated with vehicle operating cost, because fuel economy improvements benefit both variables, and with vehicle purchase price, because reductions in the price premium associated with purchasing a Prius have occurred alongside improvements in the Prius' fuel economy. While this collinearity does not affect the overall fit of regression models, it can lead to volatility in individual parameter estimates, which exhibit large changes in response to small changes in the model or data. Parameter estimates for a range of models that estimate consumer choice coefficients and socialization parameters concurrently are shown in Table 5:
Table 5: Supply Constraints Model - Socialization and Choice Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Bass Model</th>
<th>Familiarity Model</th>
<th>Supply Constraints Model</th>
<th>Supply Constraints Model + Socialization from Waitlist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant for Gasoline Vehicle</td>
<td>-</td>
<td>4.343</td>
<td>4.390</td>
<td>4.348</td>
</tr>
<tr>
<td>Purchase Price</td>
<td>-</td>
<td>0.306</td>
<td>-0.451</td>
<td>0.453</td>
</tr>
<tr>
<td>Operating Cost</td>
<td>-</td>
<td>0.035</td>
<td>-0.477</td>
<td>-0.132</td>
</tr>
<tr>
<td>Greenhouse Gas Emissions</td>
<td>-</td>
<td>-3.388</td>
<td>-0.987</td>
<td>-1.085</td>
</tr>
<tr>
<td>Coefficient of Innovation (p)</td>
<td>5.2E-05</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Coefficient of Imitation (q)</td>
<td>0.0173</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Marketing Effectiveness</td>
<td>-</td>
<td>0.002</td>
<td>0.160</td>
<td>0.005</td>
</tr>
<tr>
<td>Effective Contact Rate – Prius Drivers</td>
<td>-</td>
<td>79.251</td>
<td>-10.102</td>
<td>113.42</td>
</tr>
<tr>
<td>Effect of Waitlist Length</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-60.004</td>
</tr>
</tbody>
</table>

These results exhibit the effects of this collinearity. Contrary to expectations, the purchase price variable has a positive valence in the Familiarity and Supply Constraints+Waitlist models, yet has the expected negative valence in the Supply Constraints model. Similarly, the word-of-mouth effective contact rate from Prius drivers has the expected positive valence in the Familiarity and Supply Constraints+Waitlist model, but takes a negative valence in the Supply Constraints model. While estimating these choice coefficients directly provides the best overall fit of these models to the data, the volatility observed in individual parameter estimates prevents the direct comparison of these parameters across models. To overcome this problem, the models described in the body of this paper assume a set of constant consumer choice coefficients, taken from a leading study of the automotive market (Brownstone, Bunch et al. (2000)) that combines reveal preference and stated preference choice data.

C.3 Estimation of Confidence Intervals

The estimation of confidence intervals on parameter estimates is necessary to determine whether those parameter estimates are statistically significant. System Dynamics models often violate common statistical assumptions used to estimate confidence intervals, such as the independence and identical distribution of residual errors (Dogan 2007). Here I describe the tests undertaken to determine the appropriateness of the IID assumption for these models. Visual inspection of the model residuals indicated that autocorrelation may be present, because successive
error values took similar values. The kth lag autocorrelation \( \rho(k) \) for the residuals for \( k = 0..(N-1) \) can be estimated as (Box and Jenkins 1976):

\[
\rho(k) = \frac{\gamma(k)}{\gamma(0)} \tag{28}
\]

where \( \rho(0) = 1 \). The autocovariance \( \gamma(k) \) for lag ‘k’ is calculated as:

\[
\gamma(k) = \text{Cov}(k) = \frac{1}{N} \sum_{i=1}^{N-k} (e_i - \bar{e})(e_{i+k} - \bar{e}) \tag{29}
\]

These autocorrelation estimates are shown in Table 6. Estimates shaded in grey are statistically significant at the 95% confidence level, calculated using the Ljung-Box Q-test:

<table>
<thead>
<tr>
<th>Table 6: Box Jenkins Lag Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bass Model</strong></td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>Lag = 1</td>
</tr>
<tr>
<td>Lag = 2</td>
</tr>
<tr>
<td>Lag = 3</td>
</tr>
<tr>
<td>Lag = 4</td>
</tr>
<tr>
<td>Lag = 5</td>
</tr>
<tr>
<td>Lag = 6</td>
</tr>
<tr>
<td>Lag = 7</td>
</tr>
<tr>
<td>Lag = 8</td>
</tr>
</tbody>
</table>

Table 6 shows statistically significant autocorrelation for numerous lags for each payoff variable. The simplest autoregressive model is the AR(1) model, a first-order autoregressive model with lag = 1, which takes the form:

\[
X_t = c + \rho X_{t-1} + \epsilon_t \tag{30}
\]

where \( \epsilon_t \) is a white-noise process with zero mean and variance \( \sigma^2 \). This model is often effective, because the single time step lag autocorrelation propagates through to control for some
autocorrelation at longer time lags also. The coefficient of the AR(1) model 'ρ' for each payoff variable was estimated using the Cochrane-Orcutt method (Cochrane and Orcutt 1949), shown in Table 7:

Table 7: Cochrane-Orcutt and Durbin-Watson Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Bass Model</th>
<th>Familiarity Model</th>
<th>Supply Constraints Model</th>
<th>Supply Constraints Model + Socialization from Waitlist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cochrane Orcutt AR(1) rho</td>
<td>0.725***</td>
<td>0.656***</td>
<td>0.256***</td>
<td>0.957***</td>
</tr>
<tr>
<td>AR(1) rho</td>
<td>0.841***</td>
<td>0.937***</td>
<td>0.848***</td>
<td></td>
</tr>
<tr>
<td>Durbin Watson Test</td>
<td>d=2.108</td>
<td>d=1.956</td>
<td>d=1.444</td>
<td>d=1.289</td>
</tr>
<tr>
<td>p=0.622</td>
<td>p=0.421</td>
<td>p=0.847</td>
<td>p=0.010</td>
<td>p=0.001</td>
</tr>
<tr>
<td>p=0.000</td>
<td>p=0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For the two variants of the Supply Constraints model, the extent of autocorrelation is considerably larger for the Waiting List and Dealer Incentive errors than for Sales. For the demand-side only Familiarity and Bass models with only one payoff variable, the extent of autocorrelation observed in the Sales errors is much larger. Most importantly, we are interested in whether the AR(1) model has fully controlled for the observed autocorrelation, such that no statistically significant autocorrelation remains in the residuals of the AR(1) model. The Durbin-Watson statistic is used to test for the presence of autocorrelation. The Durbin-Watson statistic is defined as:

\[
d = \frac{\sum_{i=2}^{T} (e_i - e_{i-1})^2}{\sum_{i=1}^{T} e_i^2}
\]  

(31)

where \(d\) is defined over the range 0 to 4, and \(d=2\) indicates no autocorrelation. The Durbin-Watson test statistics indicate that the AR(1) autoregressive model effectively controls for the autocorrelation in the Sales errors in each of the four models. For the Waiting List and Dealer Incentive variables in the each of the two variants of the Supply Constraints models, the Durbin-Watson test statistics lead us to reject the null hypothesis that the errors for these variables are serially independent at the 95% confidence level, indicating that autocorrelation remains in the residuals of the AR(1) model for these variables.
Having established the presence of autocorrelation in each of these models, the non-parametric bootstrapping method described by Dogan (2007) was used to estimate confidence intervals for the socialization parameters estimated in this paper, which requires less restrictive assumptions. In the bootstrapping method, synthetic datasets are generated which exhibit these same properties as the errors resulting from the calibration process. Repeatedly calibrating the model to these synthetic datasets generates a distribution of estimates for each parameter, which reveal a confidence interval for that parameter. Despite the existence of residual autocorrelation, the AR(1) autoregressive model was used in the generation of bootstrap datasets for all variables, because the Sales data is considerably more reliable than the Waiting List and Dealer Incentive datasets, and using the AR(1) model throughout provides a simple and consistent treatment that effectively controls for the existence of autocorrelation in the most important model variable.
Appendix D: Familiarity Co-flow Structure

In the model formulation, a Co-flow structure is used in capture the transfer of Familiarity within the driver population when a driver switches platforms, as developed by Struben (2006). Co-flow structures are used in differential-equation models to account for attributes (such as Familiarity) of units (such as vehicle drivers) as those units move through a system (Sterman 2000).

The primary way that consumers become familiar with a new technology, such as the Toyota Prius, is through the socialization that occurs when an individual is exposed to marketing promoting that technology, and when an individual interacts with others in their social network, resulting in them receiving information through word-of-mouth. In this application, the dynamic accumulation of Familiarity only applies to gasoline drivers’ knowledge of the new technology, the Prius, because it is assumed that gasoline drivers have full Familiarity with gasoline vehicles, Prius drivers are assumed to have full familiarity with Prius vehicles, and Prius drivers are assumed to have full familiarity with gasoline vehicles, because of the ubiquity of gasoline vehicles.

The co-flow structure is required to account for the case where a driver of a Prius reverts to driving a gasoline vehicle. Implementing the structure developed by Struben (2006), familiarity can be usefully represented at the population level:

\[
\frac{d(F_i V_j)}{dt} = V_i \frac{dF_i}{dt} + F_j \frac{dV_j}{dt} = f_{ij}^s + f_{ij}^r
\]

When \(i = \text{gasoline} \) and \(j = \text{Prius} \), the first term \(f_{ij}^s\) represents the update in familiarity obtained through socialization, which the second term \(f_{ij}^r\) represents the transfer of familiarity that occurs when a Prius driver reverts back to the gasoline platform. In this instance, the inclusion of this co-flow structure has a negligible impact on the diffusion process given the 10-year time horizon of the simulation relative to the longer average vehicle lifetime in the model. It will become more important in future analyses of the HEV market, when increasing numbers of Prius drivers may make the choice to revert back to driving a conventional gasoline vehicle.
Appendix E: Model Code

Fleet Turnover

Installed Base \(i[\text{Technology}]\) = New Vehicles \(i[\text{Technology}]\) + Used Vehicles \(i[\text{Technology}]\)

Units: vehicles

The installed base of vehicles by technology is the sum of New Vehicles and Used Vehicles.

New Vehicles \(i[\text{Technology}]\) = \(\text{INTEG} (\text{Vehicle Sales }i[\text{Technology}] \text{- Vehicle Aging }i[\text{Technology}] \text{- New Vehicle Retirements }i[\text{Technology}] \text{,} "\text{Initial Installed Base } \text{- New Vehicles }i[\text{Technology}]\))

Units: vehicles

The stock of New Vehicles accumulates new Vehicle Sales (indexed by technology \(i\)), and declines as vehicles age, becoming Used Vehicles, or are retired due to crashes and breakdowns.

Used Vehicles \(i[\text{Technology}]\) = \(\text{INTEG} (\text{Vehicle Aging }i[\text{Technology}] \text{- Used Vehicle Retirements }i[\text{Technology}] \text{,} "\text{Initial Installed Base } \text{- Used Vehicles }i[\text{Technology}]\))

Units: vehicles

The stock of Used Vehicles accumulates the aging of vehicles that were formerly New Vehicles, and declines as used vehicles are retired due to aging.

Vehicle Sales \(i[\text{PRIUS}]\) = Dealer Prius Sales
Vehicle Sales \(i[\text{GAS}]\) = UPL US Monthly Light Vehicle Sales - Dealer Prius Sales

Units: vehicles/month

For the Prius, the rate of Vehicle Sales entering the fleet is given by the rate of Prius sales occurring at dealerships, as simulated by the model. For the conventional gasoline technology, the rate of Vehicle sales is given by the historic rate of light vehicle sales in the United State, less the rate of Prius sales simulated by the model.

Vehicle Aging \(i[\text{Technology}]\) = New Vehicles \(i[\text{Technology}]\)/Aging Time Lambda

Units: vehicles/Month

The rate of Vehicle Aging, indexed by technology, is formulated as the stock of New Vehicles by technology, divided by the assumed time for New Vehicles to age and become Used Vehicles.

New Vehicle Retirements \(i[\text{Technology}]\) = NV Discard Fr*New Vehicles \(i[\text{Technology}]\)

Units: vehicles/Month

The rate of New Vehicle Retirements due to breakdowns and crashes, indexed by platform, is equal to the stock of New Vehicles multiplied by NV Discard Fr, the fraction of New Vehicles discarded each month.

Used Vehicle Retirements \(i[\text{Technology}]\) = Used Vehicles \(i[\text{Technology}]\)/Retirement Time

Units: vehicles/Month

The rate of Used Vehicle Retirements, indexed by technology, is equal to the stock of Used Vehicles for each technology, divided by Retirement Time, the average lifetime that a vehicle survives as a Used Vehicle.

"Initial Installed Base - New Vehicles \(i[\text{GAS}]\) = 7.8e+07
"Initial Installed Base - New Vehicles \(i[\text{PRIUS}]\) = 0
"Initial Installed Base - Used Vehicles \(i[\text{GAS}]\) = 1.56e+08
"Initial Installed Base - Used Vehicles \(i[\text{PRIUS}]\) = 0

Units: vehicles

Initially, the installed base of Prius vehicles, both New and Used, is zero. Assuming a total installed base of light vehicles in the United States of 234 million vehicles, I assume that one third of these vehicles are New Vehicles, equal to 78 million, while the remaining two-thirds of these vehicles are Used Vehicles, equal to 156 million.

NV Discard Fr = 0.01/12
The rate of New Vehicle Discards due to breakdowns and crashes is assumed to be 1% per year, equal to 0.01/12 (~0.00083) per month.

Aging Time Lambda=60
Units: Month

The age at which New Vehicles age to become Used Vehicles, defined as Aging Time Lambda, is assumed to be 60 months (5 years).

Retirement Time=120
Units: Month

The age of which Used Vehicles are retired on average assumed to be 120 months (10 years). Thus, the average lifetime of a vehicle in the model is 60 + 120 = 180 months (15 years).

Units: vehicles/Month

The technology currently being driven by the buyer of a new vehicle influences their purchase decision. The number of New Vehicle Buyers who currently own a Prius depends on the fraction of vehicle buyers who currently own a New Vehicle (versus a Used Vehicle), and the fraction of Prius drivers in each of these populations. The balance of New Vehicle Buyers are assumed to drive a conventional gasoline vehicle, calculated as the historic number of light vehicle sales per month less the number of New Vehicle Buyers who drive a Prius.

Prius Driver Fr from New Vehicle Retirements and Vehicle Aging=New Vehicles [PRIUS]/SUM(New Vehicles i [Technology!])
Units: dmnl

The fraction of New Vehicle drivers who drive a Prius is given by the number of New Prius vehicles, divided by the total number of New Vehicles.

Prius Driver Fr from Used=Used Vehicles [PRIUS]/SUM(Used Vehicles i [Technology!])
Units: dmnl

The fraction of Used Vehicle drivers who drive a Prius is given by the number of used Prius vehicles, divided by the total number of Used Vehicles.

Fr New Sales from New Vehicle Drivers=0.4
Units: dmnl

The fraction of consumers buying a vehicle that currently drive a New Vehicle (i.e. less than 5 years old) is assumed to be 40%.

Customer Wait List and the Vehicle Supply Chain

Wait List= INTEG (Customer Orders-Reneging-Order Fulfilment,0)
Units: vehicles

The wait list for the Prius accumulates new customer orders for the Prius, and declines when Order Fulfillment occurs, or when consumers renege from the wait list.

Customer Demand for Prius=MAX(0, SUM(New Vehicle Buyers i [Technology!]*Prius Share of Customer Demand i [Technology!])*UPL Car Share of Light Vehicle Sales*UPL Prius Class Share of Car Segment)
Units: vehicles/Month
The level of customer demand for the Prius each month is estimated as the market share of Prius within the segment of the light vehicle market that the Prius competes in. The number of New Vehicle Buyers within the Prius segment, indexed by technology, is calculated as New Vehicle Buyers multiplied by the fraction of the light vehicles sales that are cars, multiplied by the fraction of the car market occupied by the Prius' segment. Multiplying this by the Prius Share of Customer Demand, indexed by technology, gives the demand for the Prius indexed by technology currently being driven by each buyer. Summing across these technologies gives the total Customer Demand for the Prius.

Customer Orders = Customer Demand for Prius
Units: vehicles/Month

The rate of Customer Orders at the dealership is equal to Customer Demand for the Prius.

Order Fulfillment = Dealer Prius Sales
Units: vehicles/month

The rate of Order Fulfillment from the Prius wait list is equal to the rate at which Dealer Prius Sales are completed, removing vehicles from the Dealer Inventory.

Reneging = SW Reneging * MAX(0, Wait List * Reneging Fraction)
Units: vehicles/Month

The rate of Reneging is equal to the number of customers of the Wait List, multiplied by the Reneging Fraction, the fraction of the Wait List who drop off each month. The rate of Reneging must be non-negative, because the Wait List can only be greater than or equal to zero. The switch SW Reneging allows the first-order Reneging feedback to be turned on/off.

Reneging Fraction = 0.05
Units: dmnl/Month

The rate of reneging from the wait list (customers who join the wait list but subsequently relinquish their place before their order is fulfilled) is assumed to be 5% of the number of customers on the wait list per month.

SW Reneging = 1
Units: dmnl

If SW Reneging = 1, reneging is enabled in the model. If SW Reneging = 0, reneging is disabled in the model (equivalent to the Reneging Fraction = 0).

Dealer Inventory = INTEG (Shipments to Dealers - Dealer Prius Sales, Initial Dealer Inventory)
Initial Dealer Inventory = 0
Units: vehicles

The stock of Prius vehicles in the Dealer Inventory accumulates Shipments to Dealers of Prius vehicles, and is reduced as Dealer Prius Sales transactions are completed. Initially, the Dealer Inventory of Prius vehicles is zero, as the model begins before the Prius is introduced into the US market.

Shipments to Dealers = Shipments to US
Units: vehicles/Month

The rate at which Prius vehicles are shipped to Toyota dealers, Shipments to Dealers, is equal to the rate at which Prius Shipments arrive in the US from Japan, where Prius vehicles are manufactured.

Shipments to US = DELAY3 (UPL Prius Exports to US, Shipping Delay)
Units: vehicles/Month

Shipments of Prius vehicles to the United States are assumed to follow a third-order delay of exports of Prius vehicles from Japan, accounting for the time to ship vehicles from Japan to the United States and also distribute vehicles to Toyota dealerships within the United States.

Shipping Delay = 0.75
Units: Month
The Shipping Delay time from Japan to dealerships in the United States is assumed by be 0.75 months.

Dealer Prius Sales=\text{MAX}(0, \text{MIN}(\text{Maximum Shipping Rate}, \text{Desired Shipping Rate}))

Units: vehicles/Month

The rate at which Dealer Prius Sales occur is the lesser of the rate at which Prius vehicles can be shipping from the Dealer Inventory (the Maximum Shipping Rate) and the rate at which customers can be retrieved from the wait list (the Desired Shipping Rate). The rate of Dealer Prius Sales must be non-negative, because both the Dealer Inventory and the Wait List can only be greater than or equal to zero.

Maximum Shipping Rate=\frac{\text{Dealer Inventory}}{\text{Minimum Dealer Delay}}

Units: vehicles/Month

The Maximum Shipping Rate given the available Dealer Inventory is calculated as the Dealer Inventory divided by the Minimum Dealer Delay, the minimum time needed to prepare a vehicle from the inventory for sale to a customer.

Minimum Dealer Delay=0.05

Units: Month

The Minimum Dealer Delay is assumed to be 0.05 months (~1.5 days).

Desired Shipping Rate=\frac{\text{Wait List}}{\text{Target Delivery Delay}}

Units: vehicles/Month

The Desired Shipping Rate given the current Wait List is calculated as the Wait List divided by the Target Delivery Delay, the average time needed to contact a customer from the Wait List and for that customer to visit their dealership to complete their purchase transaction.

Target Delivery Delay=0.2

Units: Month

The Target Delivery Delay is assumed to be 0.2 months (~6 days).

Inventory Coverage=\text{ZIDZ}(\text{Dealer Inventory}, \text{Sales Forecast})

Units: Month

Dealers use their estimate of their Inventory Coverage (the number of months of inventory they have on hand) to determine whether they should offer incentives to consumers to manage their inventory. Inventory Coverage is calculated as the current level of Dealer Inventory divided by the Sales Forecast.

Sales Forecast=\text{IF THEN ELSE(} \text{Time}<\text{Prius Introduction Date, 0, (Weight Dealer v Marketing}*\text{Dealer Sales Forecast})+(1-\text{Weight Dealer v Marketing})*\text{Initial Marketing Demand Forecast} )

Units: vehicles/Month

The Sales Forecast used by dealers to estimate their Inventory Coverage is the weighted average of the Dealer Sales Forecast (the forecast they make themselves based on their own experience) and the Initial Marketing Demand Forecast (the forecast provided to the dealerships by the manufacturer), where Weight Dealer v Marketing is the relative weight attached to each forecast. Prior to the introduction of the Prius, the Sales Forecast is zero.

Initial Marketing Demand Forecast=1000

Units: vehicles/Month

The Initial Marketing Demand Forecast is assumed to be 1000 vehicles/month, based on anecdotal newspaper reports.

Weight Dealer v Marketing=\text{IF THEN ELSE((Cumulative Sales/Ref Cum Sales for Dealer Forecast)<1, Cumulative Sales/Ref Cum Sales for Dealer Forecast, 1)}

Units: dmnl

The Weight Dealer v Marketing is the weight attached to the dealer forecast relative to the manufacturer's marketing forecast. The Weight Dealer v Marketing grows linearly with Cumulative Sales until the Reference Cumulative Sales for
Dealer Forecast is reached, at which point Weight Dealer v Marketing = 1. Initially, dealers have little or no experience with the Prius, so they must rely on the manufacturer’s marketing forecast until their experience accumulates with cumulative Prius sales.

Cumulative Sales= INTEG (Sales,0)  
Units: vehicles  

*Cumulative Sales of the Prius is the accumulation of monthly Sales of the Prius over time.*

Ref Cum Sales for Dealer Forecast=10000  
Units: vehicles  

*The Reference Cumulative Sales for the Dealer Forecast is assumed to be 10000 vehicles.*

Dealer Sales Forecast=(Weight Orders v Sales*Expected Sales from Customer Orders)+((1-Weight Orders v Sales)*Expected Sales from Dealer Sales)  
Units: vehicles/Month  

*When dealerships forecast their rate of Prius sales, they could look to the rate of which Prius sales are being completed, or the rate of which Customer Orders are arriving at their dealership, or both. Here, the Dealer Sales Forecast is the weighted average of Expected Sales from Customer Orders and Expected Sales from Dealer Sales.*

Expected Sales from Dealer Sales= SMOOTH N(Dealer Prius Sales, Sales Smoothing Time, Initial Marketing Demand Forecast, 3)  
Units: vehicles/Month  

*Expected Sales from Dealer Sales is assumed to be a third-order smoothing of the monthly rate of Dealer Prius Sales, smoothed over the Sales Smoothing Time. Initially, the Marketing Demand Forecast is used in the absence of historic Dealer Prius Sales to base the forecast on.*

Expected Sales from Customer Orders=SMOOTH N(Customer Orders, Sales Smoothing Time, Initial Marketing Demand Forecast, 3)  
Units: vehicles/Month  

*Expected Sales from Customer is assumed to be a third-order smoothing of the monthly rate of Customer Orders, smoothed over the Sales Smoothing Time. Initially, the Marketing Demand Forecast is used in the absence of historic Dealer Prius Sales to base the forecast on.*

Sales Smoothing Time=3  
Units: Month  

*The Sales Smoothing Time over which dealerships smooth their forecasts is assumed to be three months.*

Weight Orders v Sales=1  
Units: dmnl  

*I assume that dealerships base their dealer sales forecast exclusively on Expected Sales from Customer Orders, which is arguably a better measure of customer demand than Expected Sales from Dealer Sales, which can be biased by supply constraints.*

**Consumer Familiarity**

Familiarity with Prius=ZIDZ(Total Familiarity with Prius,Installed Base i[GAS])  
Units: dmnl  

*Familiarity is modeled using a co-flow structure to keep track of the effect of fleet turnover on consumer familiarity. The average Familiarity with Prius is calculated as the gasoline vehicle population’s Total Familiarity with the Prius, measured in vehicles, divided by the Installed Base of gasoline vehicles. This formulation implicitly assumes that the gasoline driver population is well mixed and have similar social habits.*
Total Familiarity with Prius = \text{INTEG} (\text{Familiarity Update} + \text{Total Familiarity Gain Prius} - \text{Total Familiarity Loss Prius}, \text{Initial Familiarity with Prius})

Units: vehicles

Gasoline drivers' Total Familiarity with the Prius accumulates social exposure to the Prius from marketing and word-of-mouth, Familiarity Update, plus Familiarity gained who drivers of the Prius revert to driving a gasoline vehicle, Total Familiarity Gas Prius, and decreases when drivers of gasoline vehicles adopt the Prius, Total Familiarity Loss Prius. Initially, this stock takes the value Initial Familiarity with Prius.

Initial Familiarity with Prius = 0

Units: vehicles

The Initial Familiarity drivers of conventional gasoline vehicles have with the Prius is assumed to be zero.

Familiarity Update = (\text{Familiarity Gain} - \text{Familiarity Loss}) \times \text{Installed Base [GAS]}

Units: vehicles/Month

Gasoline driver socialization and forgetting happens at the individual level. However, the co-flow structure in the model maintains Familiarity at the population level. The rate of Familiarity Update in the gasoline driver population due to socialization and forgetting is calculated as the net effect of Familiarity Gain (socialization) less Familiarity Loss (forgetting), multiplied by the Installed Base of gasoline vehicles.

Familiarity Gain = \text{Total Social Exposure to Platform} \times (1 - \text{Familiarity with Prius})

Units: dmnl/Month

Gasoline drivers gain familiarity to the Prius through social exposure, assumed to occur at a diminishing rate as socialization saturation occurs. The Familiarity Gain made by gasoline vehicle drivers as a result of social exposure to the Prius (through marketing and word-of-mouth) is calculated as the Total Social Exposure to the Prius Platform multiplied by 1-Familiarity with Prius, the remaining Familiarity potential that exists in the gasoline driver population.

Total Social Exposure to Platform = \text{Socialization Effect of Marketing} + \text{Socialization Effect of Prius Drivers} + \text{Socialization Effect of Waitlist}

Units: dmnl/Month

Total Social Exposure to the Prius is the sum of the Socialization Effect of Marketing spent on the Prius, the Socialization Effect of Prius Drivers through word-of-mouth and the Socialization Effect of the Waitlist of drivers waiting to purchase a Prius.

Socialization Effect of Marketing = \text{Prius Marketing Effectiveness} \times \text{UPL US Prius Marketing Spend/Dollars per Million}

Units: dmnl/Month

Following the standard Bass model, the Socialization Effect of Marketing is equal to the amount of marketing spent on the Prius by Toyota each month, UPL US Prius Marketing Spend, converted to millions by dividing by Dollars per Million, multiplied by the Prius Marketing Effectiveness coefficient.

Prius Marketing Effectiveness = 0

Units: dmnl/million

The Prius Marketing Effectiveness is a parameter estimated empirically, assuming constant returns on marketing effort.

Dollars per Million = 1e+06

Units: $/million

Dollars per Million is equal to 1 million, used to convert from dollars to millions of dollars.

Socialization Effect of Prius Drivers = \text{Probability of Contact with Prius Driver} \times \text{Effective Contact Rate Prius Drivers}

Units: dmnl/Month

Inspired by the word-of-mouth formulation in the Bass model, the Socialization Effect of Prius Drivers is the product of the rate at which effective contacts occur in the community, the Effective Contact Rate Prius Drivers, and the likelihood that
those contacts are with Prius drivers, the Probability of Contact with Prius Drivers. As in the Bass model, this formulation assumes that gasoline vehicle drivers and Prius vehicle drivers are well mixed in the community.

Probability of Contact with Prius Driver = \frac{\text{Installed Base}_i[\text{PRIUS}]}{\sum \text{Installed Base}_i[\text{Technology}!]}  
Units: \text{dmnl}

The Probability of Contact with a Prius Driver is equal to the Installed Base of Prius vehicles, divided by the total Installed Base of vehicles of all technologies.

Effective Contact Rate Prius Drivers = \text{E}
Units: \text{dmnl/Month}

The Effective Contact Rate with Prius Drivers is the net rate at which contacts between potential adopters and adopters results in adoption of the Prius. This parameter represents the net effect of the contact rate and adoption rate parameters in the standard Bass model. This parameter is estimated empirically.

Socialization Effect of Waitlist = \text{WL Coefficient} \times \text{UPL Waitlist Length}
Units: \text{dmnl/Month}

The Prius case demonstrates that the existence of a Waitlist can generate considerable media attention. The Socialization Effect of the Waitlist is estimated as the length of the Waitlist (in months), multiplied by WL Coefficient, the socialization effect per month of wait list length.

WL Coefficient = \text{E}
Units: \text{dmnl/(Month*Month)}

The wait list socialization coefficient WL Coefficient is a parameter estimated empirically, assuming a linear effect of wait list length (months) on socialization.

Familiarity Loss = \text{Effect of Social Exposure on Forgetting} \times \text{Familiarity with Prius} \times \text{Normal Forget Rate} \Phi
Units: \text{dmnl/Month}

Drivers of gasoline vehicles may forget about the Prius if they do not receive regular social exposure to the new technology. The rate of Familiarity Loss is calculated as the current level of Familiarity with the Prius, multiplied by the assumed Normal Forget Rate \Phi, multiplied by the Effect of Social Exposure on Forgetting.

Effect of Social Exposure on Forgetting = 1 - \left[ 0 + (1-0) \times \exp(4 \times \text{Epsilon} \times (\text{Total Social Exposure to Platform-Social Exposure Offset EtaRef})/(1+\exp(4 \times \text{Epsilon} \times (\text{Total Social Exposure to Platform-Social Exposure Offset EtaRef}))) \right]
Units: \text{dmnl}

Here I suggest the Effect of Social Exposure on Forgetting is non-linear: consumers are likely to forget about the Prius more quickly when their level of Familiarity with the Prius is low; conversely, their rate of forgetting is likely to be low when their level of Familiarity is high. Here the Effect of Social Exposure on Forgetting is formulated as a decreasing logistic function with parameters Epsilon and Social Exposure Offset EtaRef. When Familiarity approaches 0, the Effect of Social Exposure on Forgetting approaches 1. When Familiarity approaches 1, the Effect of Social Exposure on Forgetting approaches 0.

\text{Epsilon} = 20
Units: Month

The forgetting parameter Epsilon is assumed to be 20.

Social Exposure Offset EtaRef = 0.05
Units: \text{dmnl/Month}

The forgetting parameter Social Exposure Offset EtaRef is assumed to be 0.05.

\text{Normal Forget Rate} \Phi = 0.025
Units: \text{dmnl/Month}

The rate at which gasoline drivers lose Familiarity with the Prius due to forgetting, the Normal Forget Rate \Phi, is assumed to be 0.025 (2.5% per month).
Total Familiarity Gain Prius = Familiarity of Prius Discarders * Discards Prius to Gas
Units: vehicles/Month

*When a driver who currently drives a Prius reverts back and buys a gasoline vehicle, the installed base of gasoline vehicles is increased by one (assuming the Prius vehicle is retired), and the population of gasoline vehicle drivers gains the Familiarity with the Prius that driver had.* Here the Total Familiarity Gain each month as a result of this fleet turnover is calculated as the number of Discard Prius to Gas per month, multiplied by the Familiarity with the Prius of those drivers.

Discards Prius to Gas = \( \sum (\text{Share}_{ij} [\text{Technology}, \text{TechnologyTo}]) \times \text{Select Prius to Gas}[\text{Technology}, \text{TechnologyTo}] \times \text{Prius Discard Fr} \times \text{Size of Prius Market} \)
Units: vehicles/Month

*The number of Discard Prius to Gas, in vehicles/month, is equal to the Size of the Prius Market, multiplied by the fraction of those drivers who currently drive a Prius, Prius Discard Fr, multiplied by the share of those Prius drivers who chose to revert to a gasoline vehicle, calculated by multiplying Select Prius to Gas with Share \( ij \) and summing across all technologies.*

Select Prius to Gas[Technology, TechnologyTo] = IF THEN ELSE (TechnologyTo=GAS AND Technology=PRIUS, 1, 0)
Units: dmnl

Select Prius to Gas is a binary variable that identifies drivers currently driving a Prius who revert back to the conventional gasoline vehicle. It takes the value 1 if Technology = PRIUS and TechnologyTo=GAS, and 0 otherwise.

Prius Discard Fr = \( \text{New Vehicle Buyers \( i \) [PRIUS]} / \sum (\text{New Vehicle Buyers \( i \) [Technology]}) \)
Units: dmnl

*The Prius Discard Fraction is the number of New Vehicle Buyers who currently drive a Prius, divided by the total number of New Vehicle Buyers across all technologies.*

Familiarity of Prius Discarders = 1
Units: dmnl

*The Familiarity of Prius Discarders is assumed to be one, because these drivers have experienced the Prius firsthand, providing the opportunity to learn the unique attributes of this technology.*

Total Familiarity Loss Prius = \( \max(0, \text{Familiarity with Prius} \times \text{Sales Prius from Gas}) \)
Units: vehicles/Month

*When a driver who currently drives a gasoline vehicle buys a Prius, the installed base of gasoline vehicles is decreased by one (assuming the gasoline vehicle is retired), and the population of gasoline vehicle drivers lose the Familiarity with the Prius that driver had.* Here the Total Familiarity Loss each month as a result of this fleet turnover is calculated as the number of Sales Prius from Gas per month, multiplied by the Familiarity with the Prius of those drivers.

Sales Prius from Gas = \( \sum (\text{Share}_{ij} [\text{Technology}, \text{TechnologyTo}]) \times \text{Select Gas to Prius}[\text{Technology}, \text{TechnologyTo}] \times \text{Gas Discard Fr} \times \text{Size of Prius Market} \)
Units: vehicles/Month

*The number of Sales Prius from Gas, in vehicles/month, is equal to the Size of the Prius Market, multiplied by the fraction of those drivers who currently drive a gasoline vehicle, Gas Discard Fr, multiplied by the share of those drivers who chose to purchase a Prius, calculated by multiplying Select Gas to Prius with Share \( ij \) and summing across all technologies.*

Size of Prius Market = \( \text{UPL} \times \text{US Monthly Light Vehicle Sales} \times \text{UPL Car Share of Light Vehicle Sales} \times \text{UPL Prius Class Share of Car Segment} \)
Units: vehicles/Month

*The Size of the Prius Market each month is equal to the total number of light vehicle sales in the United States per month, \( \text{UPL US Monthly Light Vehicle Sales} \), multiplied by the car share of the light vehicle market each month, \( \text{UPL Car Share of Light Vehicle Sales} \), multiplied by the size of the segment the Prius is competing in, \( \text{UPL Prius Class Share of Car Segment} \). The first generation Prius was a Compact Car, while the second and third generation Prius vehicles are Mid-size Cars.*

Gas Discard Fr = \( \text{New Vehicle Buyers \( i \) [GAS]} / \sum (\text{New Vehicle Buyers \( i \) [Technology]}) \)
The Gas Discard Fraction is the number of New Vehicle Buyers who currently drive a gasoline vehicle, divided by the total number of New Vehicle Buyers across all technologies.

Select Gas to Prius[Technology,TechnologyTo]=IF THEN ELSE(Technology=GAS AND TechnologyTo=PRIUS, 1, 0)  
Units: dmnl

Select Gas to Prius is a binary variable that identifies drivers currently driving a gasoline vehicle who switch to the Prius. It takes the value 1 if Technology = GAS and TechnologyTo=PRIUS, and 0 otherwise.

Vehicle Utility and Vehicle Market Share

Prius Share of Customer Demand ij[Technology]=IF THEN ELSE(Time<Prius Introduction Date, 0, SUM(Share ij[Technology,TechnologyTo]*Matrix Entrant Selection ij[Technology,TechnologyTo])))  
Units: dmnl

The Prius Share of Customer Demand is the percentage market share of the Prius, indexed by the technology i currently being used by drivers. Prius to the Prius Introduction Date, the Prius market share is zero. The market Share is multiplied by the Matrix Entrant Selection variable, zeroing the Share of technologies where the technology is not the Prius. Summing across technology j (TechnologyTo) results in the Prius Share of Customer Demand by the technology i currently being driven by the customers.

Share ij[Technology,TechnologyTo]=Affinity ij[Technology,TechnologyTo]/SUM(Affinity ij[Technology,TechnologyTo]))  
Units: dmnl

The market Share of technology j for owners of technology i is estimated as the Affinity they have with technology j, divided by the sum of the Affinity they have with all technologies.

Affinity ij[Technology,TechnologyTo]=Familiarity ij[Technology,TechnologyTo]*EXP Utility ij[TechnologyTo]  
Units: dmnl

The Affinity that drivers of technology i have with technology j is equal to the Familiarity drivers of technology I have with technology j, multiplied by the exponential of the utility of technology j.

EXP Utility ij[TechnologyTo]=EXP(Utility ij[TechnologyTo])  
Units: dmnl

EXP Utility is equal to the exponential of the utility of technology j. This intermediate step is calculated before the effect of Familiarity is incorporated, to ensure that the choice formulation is globally robust to negative utility values.

Familiarity ij[Technology,TechnologyTo]=IF THEN ELSE(Technology=GAS AND TechnologyTo=PRIUS, IF THEN ELSE( SW Endogenous Familiarity=0, Exogenous Familiarity Value, Familiarity with Prius), 1)  
Units: dmnl

The Familiarity that drivers of technology i have with technology j depends on the specific combination of technologies i and j. I assume that all drivers are fully familiar with the conventional gasoline technology (i.e. Familiarity ij[Technology][GAS]=1). I also assume that drivers who have already adopted the Prius are fully familiar with the Prius (i.e. Familiarity ij[PRIUS][PRIUS]=1). Therefore, the familiarity dynamics calculated by the model, Familiarity with Prius, only applies in the case where Technology=GAS and TechnologyTo=PRIUS.

Matrix Entrant Selection ij[Technology,TechnologyTo]=IF THEN ELSE(TechnologyTo=PRIUS, 1, 0)  
Units: dmnl

The variable Matrix Entrant Selection is a matrix of binary variables used to signify when the technology being considered (TechnologyTo) is the Prius.

Utility ij[TechnologyTo] = U1 ij[TechnologyTo]+U2 ij[TechnologyTo]+U3 ij[TechnologyTo]+U4 ij[TechnologyTo]+U5 ij[TechnologyTo]  
Units: dmnl
The Utility of technology \( j \) is the sum of the effect of the observable attributes of each technology: Purchase Price \( (U_1) \), Operating Cost \( (U_2) \), Acceleration \( (U_3) \), Range \( (U_4) \) and Greenhouse Gas Emissions \( (U_5) \).

Prius Introduction Date = 5
Units: Month

The Prius is introduced into the market in Month 5 (May 2000).

SW Endogenous Familiarity = 1
Units: dmnl

If SW Endogenous Familiarity = 1, Familiarity is calculated endogenously in the model. If SW Endogenous Familiarity = 0, the Exogenous Familiarity Value is used.

Exogenous Familiarity Value = 1
Units: dmnl

The Exogenous Familiarity Value is the level of familiarity assumed if SW Endogenous Familiarity = 0. Exogenous Familiarity Value = 1 represents full information, as in the economically rational model of decision-making.

\[ U_1(\text{TechnologyTo}) = \left( \frac{\text{Effective Price } j[\text{TechnologyTo}]}{1000} \right) / \ln(\text{Household Income}) \times \text{Purchase Price Weight} \]
Units: dmnl

The effect of the purchase price of technology \( j \) on utility, \( U_1 \), is formulated as a function of both the effective purchase price of the technology and the household income of the consumer. Specifically, \( U_1 \) is estimated as the Effective Price of technology \( j \) (in thousands of dollars), divided by the natural log of Household Income (in thousands of dollars), multiplied by the Purchase Price Weight. Taking the natural log of Household Income captures the concept that consumers become less sensitive to price as their income increases.

Purchase Price Weight = -0.361
Units: dmnl/($/vehicles)

Purchase Price Weight is assumed to be -0.361 (Brownstone, Bunch et al. 2000).

Effective Price \( j[\text{PRIUS}] = UPL_{\text{MSRP}} j[\text{PRIUS}] - UPL_{\text{Federal Tax Credit - Prius}} - UPL_{\text{State Government Incentives - Prius}} - \text{Dealer Incentive} \)

Effective Price \( j[\text{GAS}] = UPL_{\text{MSRP}} j[\text{GAS}] \)
Units: $/vehicles

The Effective Price of the Prius is assumed to be the Manufacturers Suggested Retail Price (MSRP) less applicable Federal and State government incentives and any incentive offered by the Toyota dealership. The Effective Price of the conventional gasoline vehicle is assumed to simply be the Manufacturers Suggested Retail Price.

Emissions Fr Weight = -0.149
Units: dmnl

Emissions Fr Weight is assumed to be -0.149. This assumption is the average of the Stated and Revealed preference coefficient estimates from Brownstone, Bunch et al. (2000).

\[ U_2(\text{TechnologyTo}) = \text{Operating Cost Weight} \times \text{Operating Cost } j[\text{TechnologyTo}] \]
Units: dmnl

The effect of operating on utility of technology \( j \), \( U_2 \), is equal to the operating cost of technology \( j \) in cents per mile, multiplied by the weight placed on this attribute, Operating Cost Weight.

Operating Cost \( j[\text{TechnologyTo}] = \left( \frac{UPL_{\text{US Average Retail Gasoline Price}}}{UPL_{\text{MPG (Combined)}}} \right) j[\text{TechnologyTo}] \)
Units: cents/miles

The Operating Cost of technology \( j \) (cents/mile) is calculated as the US Average Retail Gasoline Price (in cents/gallon) divided by the fuel economy of technology \( j \) (miles/gallon).
Operating Cost Weight = -0.17
Units: dmnl/(cents/miles)

Operating Cost Weight is assumed to be -0.17 (Brownstone, Bunch et al. 2000).

\[ U_3[j\text{[TechnologyTo]}] = \text{Acceleration Weight} \times \text{UPL Acceleration j[TechnologyTo]} \]
Units: dmnl

The effect of vehicle acceleration on utility of technology \( j \), \( U_3 \), is equal to the 0-30 acceleration of technology \( j \) in seconds, multiplied by the weight placed on this attribute, Acceleration Weight.

Acceleration Weight = -0.149
Units: dmnl/seconds

Acceleration Weight is assumed to be -0.149 (Brownstone, Bunch et al. 2000).

\[ U_4[j\text{[TechnologyTo]}] = \begin{cases} \text{IF THEN ELSE(UPL Range j[TechnologyTo]>r_{max}, U_{max}, (Range Weight A \times \text{UPL Range j[TechnologyTo]}/\text{Miles per 100 Miles}) + ((Range Weight B \times \text{UPL Range j[TechnologyTo]}/\text{Miles per 100 Miles})^2))} \\ \end{cases} \]
Units: dmnl

Consistent with Brownstone, Bunch et al. (2000), the effect of vehicle range on utility, \( U_4 \), is assumed to increase as vehicle range, but at a decreasing rate. BB&T model this using a negative quadratic function, where Range Weight A takes a positive value and Range Weight B takes a negative value. To make this formulation globally robust, if the range of technology \( j \) exceeds \( r_{max} \), the range value at which the quadratic is at its maximum, I assume the maximum utility value \( U_{max} \).

Range Weight A = 1.268
Units: dmnl/hundred miles

Range Weight A is assumed to be 1.268 (Brownstone, Bunch et al. 2000).

Range Weight B = -0.116
Units: dmnl/(hundred miles*hundred miles)

Range Weight A is assumed to be -0.116 (Brownstone, Bunch et al. 2000).

\( r_{max} = 546.552 \)
Units: miles

\( R_{max} \) is assumed to be 546.552, derived from the values of Range Weight A and Range Weight B.

\( U_{max} = 3.46514 \)
Units: dmnl

\( U_{max} \) is assumed to be 3.46514, derived from the values of Range Weight A and Range Weight B.

Miles per 100 Miles = 100
Units: miles/hundred miles

This units correction is used to convert miles to hundreds of miles, as used in the range formulation specified by Brownstone, Bunch et al. (2000).

\[ U_5[j\text{[TechnologyTo]}] = \text{Emissions Fr Weight} \times \text{UPL Emissions Fraction j[TechnologyTo]} \]
Units: dmnl

The effect of greenhouse gas emissions on the utility of technology \( j \), \( U_5 \), is equal to the Emissions Fraction Weight multiplied by the greenhouse gas emissions by technology, measured as annual greenhouse gas emissions as a fraction of the annual greenhouse gas emissions of an equivalent gasoline vehicle.
Dealer Incentive = IF THEN ELSE (SW UPL Incentives for Testing=1, UPL Dealer Incentives, IF THEN ELSE(Days to Turn<=0, 0, MAX(0, Max Dealer Incentive - Coefficient*(Days to Turn^PPower))))
Units: $/vehicles

The Dealer Incentive offered for the Prius is formulated using a standard power-law, capturing the non-linear response between inventory coverage (Days to Turn) and the incentive offered. As the Days to Turn each Prius vehicle increases, greater incentives are needed to sell the vehicle in order to manage dealer inventory. First I assume that a Maximum Dealer Incentive exists, representative of the difference between the MSRP and the Dealer Invoice price the dealer paid for the vehicle. The Dealer Incentive is calculated as the Max Dealer Incentive less the profit made by the dealer, calculated as a power-law based on Days to Turn with power PPower.

PPower=-0.69
Units: dmnl

The power law parameter PPower is assumed to be -0.69, based on empirical analysis of Prius transaction data.

Coefficient=7256
Units: $/vehicles

The power law parameter Coefficient is assumed to be 7256, based on empirical analysis of Prius transaction data.

Max Dealer Incentive=3000
Units: $/vehicles

The maximum incentive offered by dealers to encourage sales of the Prius is assumed to be $3,000, representative of the average difference between the Manufacturer’s Suggested Retail Price for the Prius and the Dealer Invoice price charged to dealers when they purchase inventory.

SW UPL Incentives for Testing=0
Units: dmnl

If SW UPL Incentives for Testing=0, the Dealer Incentive is calculated endogenously in the model. If SW UPL Incentives for Testing=0, the historic Prius Dealer Incentive data uploaded into the model is used.

Days to Turn=Inventory Coverage*Correction Dmnl Days per Month
Units: days

The average number of days needed to turn over a vehicle in the dealer’s inventory (that is, the difference between the sale date and the date the vehicle was delivered to the dealer) is equal to the current Inventory Coverage in months, multiplied by the number of Days per Month, to convert to days.

Correction Dmnl Days per Month=30
Units: days/Month

This units correction is used to convert inventory coverage, measured in months, to days for the dealer incentive calculation.
Essay 2: Understanding Spatiotemporal Patterns of Hybrid-Electric Vehicle Adoption in the United States

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Abstract:
Over 2 million hybrid-electric vehicles have been sold in the United States since their introduction over a decade ago. Diffusion is not uniform: sales are clustered in particular regions such as the West Coast, around Washington DC and north into New York and New England. Here I explore the extent to which these adoption patterns are explained by two alternative theories: 1) market heterogeneity, due to factors such as regional variation in government incentives, gasoline prices and consumer demographics; and 2) social contagion, as information about the innovation spreads through consumers' social networks; in particular, the extent to which social contagion is primarily local, or whether links between geographically distant nodes play an important role in adoption. I develop a formal model of spatial technology diffusion capturing the generation of information among regions through people's social networks. The model is applied to the case of the diffusion of the Toyota Prius hybrid-electric vehicle in the United States. I find that regional variation in adoption rates is primarily explained social contagion through local, experiential interactions, amplifying underlying heterogeneity in consumer adoption thresholds. The impact of long-range links in social networks appears to be small. I discuss implications of the findings for the development of effective public policies for government agencies, effective marketing and distribution strategy for auto OEMs, and the emerging market for electric vehicles and EV recharging infrastructure.
1. Introduction

Hybrid-electric vehicles such as the Toyota Prius have been available in the United States for over a decade. Hybrid-electric vehicles (hereafter referred to as 'hybrid vehicles'), and now plug-in electric vehicles ('plug in electrics' such as the Chevrolet Volt and Nissan Leaf), are the latest of several waves of alternative vehicle technologies aimed at reducing negative externalities associated with the dominant fossil fuel-powered internal combustion auto design, including energy security, greenhouse gas emissions, and particulate air pollution. Hybrid vehicles achieve improved fuel economy by combining a conventional gasoline internal combustion engine with an electric motor powered by electricity generated during vehicle braking. Understanding the factors influencing consumer adoption of this technology and its diffusion into the vehicle fleet is critical if future energy and environmental policy goals are to be achieved (Kammen, Arons et al. 2008; Struben and Sterman 2008; Williams, DeBenedictis et al. 2012).

The Toyota Prius has dominated the hybrid vehicle market, accounting for more than 1 million of the 2 million hybrid vehicles sold in the United States since 2000 (WardsAuto 2011). However, the Prius adoption varies widely across the US (Figure 1), with high rates of adoption clustered in a small number of regions. The Prius has achieved market shares of over 7% of new light vehicle sales in some counties of California and Washington State, yet achieved no more than 1.5% market share anywhere in Louisiana, Alabama, North Dakota and Mississippi. Interestingly, this spatial variation in adoption rates can also be observed at the local level. In the San Francisco Bay Area (Figure 2), considerable Prius adoption occurred in the City of San Francisco, the City of Berkeley and around Palo Alto, even though negligible Prius adoption has occurred in Daly City and Hayward, less affluent urban areas that lie in-between. Understanding what motivates these spatial patterns of hybrid vehicle adoption has potentially important implications for where marketing effort and government incentives should be targeted to accelerate adoption.
Figure 16: Prius Market Share by County - United States

Data Source: (Polk 2010)

Figure 17: Prius Market Share by ZIP Code - San Francisco Bay Area

Data Source: (Polk 2010)
Two compelling theories exist to explain clustered patterns of hybrid vehicle adoption. The first theory is that regional markets for hybrid vehicles are heterogeneous, suggesting that hybrid vehicles are inherently more attractive in some markets over others. This variation may be due to factors that influence the economics of hybrid vehicles, such as government incentives and gas prices, or demographic factors that make consumers relatively more attracted to the attributes of hybrid vehicles, such as income, education, age and environmental preferences. The second theory is that adoption of hybrid vehicles is strongly conditioned by social contagion, meaning that a consumer may be more likely to purchase a hybrid vehicle if others in their social network have previously purchased one. The contagion theory suggests that car buyers are socially conditioned by seeing hybrid vehicles on the roads in their neighborhood, and hearing the first-hand experiences of their friends and colleagues who drive hybrid vehicles, so become more willing to consider the purchase of a hybrid. Contagion creates positive feedbacks that can amplify initially small, random variations in adoption to create substantial inhomogeneity at various scales.

Research on the aggregate (national level) diffusion of the Prius in the United States in Essay 1 established the role of social contagion in the overall growth in Prius sales over time. Here I disaggregate the national-level model developed in prior work to explore the following research question: what are the determinants of adoption of the Toyota Prius, both dynamically and spatially? Specifically, what are the relative roles of market heterogeneity and social contagion in conditioning the diffusion process observed? To do so, I develop a spatio-temporal model of technology diffusion that incorporates socio-demographic, economic, and social network factors, and use it to examine the extent to which each type of factor, including alternative social network structures, best explain the observed patterns of Prius adoption.

First, I explain how the model captures both the socio-economic factors that influence consumers' adoption threshold within a particular region, and the generation of information among regions. Second, I apply to model to the diffusion of Toyota's Prius hybrid-electric vehicle in the United States, finding that both theories contribute to the adoption clustering observed. Third, I use the model to analyze the effectiveness of Toyota's geographic marketing strategy for the Prius, finding that marketing that targets strategically selected regional market to be most effective in the presence of heterogeneous markets.

2. Heterogeneity and Contagion as Causes of Adoption Clustering

The analysis of spatial diffusion patterns in human systems has been a topic of interest in many fields, from the diffusion of tractors in farming communities (Mahajan and Peterson 1979) to
the spread of mobile phone viruses (Wang, Gonzalez et al. 2009), Twitter adoption (Toole, Cha et al. 2012) and disease outbreaks (Viboud, Bjornstad et al. 2006). In the diffusion of the Prius, characteristic S-shaped adoption curves are observed within individual regions, but variation exists in the rate of adoption between different regions, with clustering of adoption rates observed at both the national and local levels. S-shaped adoption of durable goods over time can be explained by both social contagion and adoption threshold heterogeneity (Van den Bulte and Stremersch 2004). I extend these arguments to examine the causes of spatial-temporal adoption clustering. For example, clustering may result from contagion through consumers' social networks spatially, as consumers become familiar with the Prius. Clustering may also result from heterogeneity in factors that influence the appeal of the Prius, where the factors themselves are clustered regionally. I explore these theories using evidence from the market for the Toyota Prius hybrid vehicle in the United States.

2.1. Source of Market Heterogeneity

Gasoline Prices: The financial benefit of reducing fuel consumption by adopting a hybrid vehicle is directly proportional to the price of gasoline. The price of gasoline has risen steadily over the past decade but with considerable variability, shown in Figure 3, influenced by market forces including rising global demand for oil (EIA 2012), geopolitical conflict in oil-producing countries, and economic instability. The price of gasoline also varies considerably within the United States (Figure 4), influenced by factors including state taxes (Figure 5) and proximity to oil refineries. In August 2012, state gasoline prices ranged from $3.39/gallon in Arizona to more than $4/gallon in California, Illinois and Hawaii, with an average price of $3.69/gallon and a standard deviation of $0.19/gallon.
Figure 18: US Retail Average (Real) Gasoline Price (EIA 2012)

Figure 19: Geographic Gas Price Variation - January 2011 (GasBuddy.com 2011)
Government Incentives: Numerous incentives have been offered by governments to incentivize the adoption of hybrid vehicles. At the Federal government level, hybrid vehicle incentives included a $2,000 tax deduction in years 2004-2005, and a tax credit of up to $3,150 for 60,000 hybrid vehicles per manufacturer from 2006. However, twenty-three state governments also offered incentives, ranging from reduced rate vehicle registration and exemption from air pollution testing to single-occupant HOV lane use. While the average state incentive was only $43 (estimated), the average range of incentives offered across between states was $938 (estimated). A detailed description of these incentives is provided in Appendix B.

Consumer Demographics: The extensive discrete choice literature has demonstrated the influence consumer demographics have on vehicle purchase decisions (Brownstone, Bunch et al. 2000; Berry, Levinsohn et al. 2004; Train and Winston 2007). For example, consumers' sensitivity to a vehicle's purchase price is conditioned by their income, because more affluent consumers have more discretionary income and are less sensitive to higher prices. Evidence from the hybrid vehicle market reflects the influence of consumer demographics on buying habits. Demographic profiles of US Prius buyers over the past decade reveal that Prius buyers are more often male, older, better educated and have a relatively high income (J.D. Power and Associates 2010) compared to the
average car buyer, trends consistent with the results of a survey of Prius buyers conducted in the United Kingdom (Ozaki and Sevastyanova 2011). Interviews with hybrid vehicle adopters reveal a number of motivations that led them to purchase a hybrid vehicle: 1) environmental stewardship; 2) opposition to war; 3) personal financing savings; 4) reducing dependence on foreign oil; and 5) the embrace of new technology (Heffner, Kurani et al. 2007). Communities tend to stratify by demographics including race, age, religion, education, occupation and gender (Marsden 1987; Kalmijn 1998; Louch 2000; McPherson, Smith-Lovin et al. 2001), a behavior known as homophily, explaining why geographic clustering of adoption may be observed. Higher rates of hybrid vehicle adoption are to be expected in communities with more high income, well educated, environmentally conscious consumers.

Driving Patterns and Vehicle Needs: Considerable regional variation exists in consumer driving patterns and vehicle needs for which hybrid vehicles in general, and the Prius in particular, will be more or less useful. Average annual miles of travel per driver vary widely by state, from less than 8,000 miles/year in the District of Columbia to over 15,000 miles/year in New Hampshire and Wyoming (DOE 2011). The potential benefits of the hybrid-electric powertrain (such as automatic stop-start and regenerative braking) are best realized in urban traffic and in hilly terrain, suggesting that hybrids will be more attractive to drivers in these areas. Further, most hybrid vehicle models in the market over the past decade including the Toyota Prius are passenger vehicles, not well suited to commercial applications such as farm work in rural areas or to consumers who prefer a large SUV.

Marketing Exposure: Toyota spent an estimated $276 million marketing the Prius over the past decade (Kantar Media 2010) to build consumer familiarity with the Prius. While much of this spending ($239 million) occurred in national media outlets, through a range of channels including magazines, television, internet and newspapers, considerable variation exists in Toyota’s regional marketing spending. While many states received no regional marketing, 27% of Toyota’s regional marketing budget was spent in California, (home to approximately 12% of the US population), 19% was spent in New York (home to approximately 6% of the US population) and 5% was spent in Massachusetts (home to approximately 2% of the US population). I do not consider the spillover of marketing exposure between regions, but it is reasonable to expect that this does occur. For example, much of New Hampshire’s population lives near the Massachusetts border, and would have access to major Boston television stations. It is also important to note that regional marketing spending is endogenous, to the extent that Toyota would logically target marketing spending in
regions where they consider consumers to be most likely to adopt a Prius, providing the greatest return on marketing effort.

**Vehicle Availability:** The search cost car buyers face to find a particular vehicle with the features, color, and options they desire differs based on their proximity to dealerships and the availability of vehicle models in those dealerships. Toyota has approximately 1,200 dealerships in the United States (Toyota 2012). The average state has one Toyota dealership for each 226,000 people, ranging from one dealership for each 78,000 people in Wyoming to one dealership for each 388,000 people in Arizona. More important still is the distance of each consumer to a Toyota dealership, which may explain why more dealerships are located in Wyoming given low population density. Details of how Toyota allocated vehicles to these dealerships over the last decade were not available for this study. However, a common practice in the industry is to allocate available inventory in proportion with recent sales, such as each dealership has approximately equal inventory coverage (MotorsForum.com 2009).

### 2.2. Social Contagion

The innovation diffusion literature provides a competing explanation for why clustering of hybrid vehicle adoption may occur: the uneven spread of information through social networks. The prevailing theory to explain why cumulative adoption of successful innovations commonly follows an S-shaped curve is that information about innovations is communicated through people’s social networks over time, allowing individuals to learn about that innovation, and, subsequently, decide whether to adopt (Bass 1969; Geroski 2000; Rogers 2003). Evidence from a trial of plug-in hybrid-electric vehicles supports this theory, finding that interpersonal influence within a consumer’s social network played an important role in that consumer’s perception of the new technology (Axsen and Kurani 2011). Clustering can occur organically during contagions as adoption of the innovation propagates within individuals’ social networks through word of mouth and direct social exposure, radiating out from early adopters. Of course, word-of-mouth need not be favorable. The perceived failure of a newly introduced product can be self-fulfilling, if the spread of early criticism prevents other consumers from trying or learning about the innovation themselves, leading to its ultimate demise. Examples of such failures include Coca-Cola’s ‘New Coke’ reformulation in 1985, and Microsoft’s Zune portable music player, suggesting that modeling the valence of word-of-mouth, not only its incidence, is important. When word-of-mouth is unfavorable, behavior is dominated by negative feedback, quenching the epidemic of adoption, but leaving people in a state
susceptible to a new outbreak of adoption in future. This is in contrast with the classic diffusion story where favorable word-of-mouth dominates, where positive feedback leads to a broad scale epidemic that eventually burns out due to market saturation.

The rate of adoption of innovations is governed by several factors, including: 1) the relative advantage of the innovation; 2) its compatibility with existing systems, values and behaviors; 3) the complexity of the innovation to use; 4) its trialability, facilitating experimentation; and 5) the extent to which adoption and the benefits of the innovation of the innovation are observable to others (Rogers 2003). When an innovation is obviously advantageous, compatible with existing systems, simple, easy to try and readily observed in use, little reinforcement is required from respected others to adopt the innovation. An example of such an innovation is Apple's iPod music player. In contrast, when the advantages of adoption are smaller, compatibility is an issue, the innovation is complex or hard to try, or the benefits of the innovation are hard to observe, adoption, if it occurs at all, will only occur after a period of social exposure, such as word-of-mouth from trusted others and first-hand experiences. Like other innovative vehicle technologies, the Toyota Prius is more like the latter than the former. The Toyota Prius offers excellent fuel economy, is compatible with the existing ubiquitous gasoline station infrastructure and is easily identified by its distinctive styling. However, the Prius' hybrid powertrain costs approximately $5,000 more than an equivalent gasoline vehicle (Bandivadekar, Bodek et al. 2008), yielding a slow financial payback from fuel cost savings, has a different driving feel compared to conventional gasoline vehicles, and is not easily trialed, except at a Toyota dealership or with a trusted friend, and these test drives will necessarily be short and unrepresentative of the ownership experience. Further, with its centrality to everyday life, high cost, and with an average first ownership period of almost 6 years (Polk 2012), buying a car is a far more consequential decision than the decision to buy, say, an iPod. I therefore expect that the decision to purchase a Prius is likely to require substantially more information, social exposure, and recommendations from trusted members of your social network than many other products.

Network research shows that the structure (topology) of a social network can also have a profound impact on the collective pattern of diffusion observed. The existence of long ties to distant individuals can, in some settings, accelerate the diffusion of information, traveling a greater social distance and reaching a larger number of individuals (Granovetter 1973; Watts and Strogatz 1998). However, Centola and Macy (2007) find that in 'complex' contagions, so-called because reinforcement from multiple sources is required for adoption, long ties can be a structural weakness, inhibiting the ability for reinforcement to occur. In these complex contagions, 'wide
bridges', the existence of numerous ties between nodes, facilitate the reinforcement from multiple sources needed to foster diffusion.

3. Model Formulation

The model described here draws heavily on the aggregate model of new product diffusion developed by Keith, Sterman et al. (2011), which captures both supply constraints and price feedback from new product inventory, hereafter denoted "the aggregate model". The aggregate model, summarized in Figure 4, captures four key aspects of the diffusion of durable innovations: 1) the growth of consumer familiarity through marketing and word-of-mouth; 2) the relative attractiveness of the new technology, relative to the conventional technology, represented using a logit model of discrete consumer choice; 3) the role of supply constraints on the process of diffusion, including the existence of waiting lists to adopt; and 4) the effect that inventory availability has on the price of the new technology.

![Figure 21: Structure of Aggregate Hybrid Vehicle Diffusion Model (Keith, Sterman et al. 2011)](image)

In the aggregate model, the market share of the new technology is influenced by both the utility of that technology, determined by its observable attributes, and the extent to which consumers are sufficiently familiar with that technology such that it enters their purchase
consideration set. As the installed base of the new technology grows, so does the word-of-mouth about and direct social exposure to the new technology, building consumer familiarity and further sales, a reinforcing feedback. However, as the number of adopters of the technology grows, the remaining pool of potential adopters shrinks, creating a balancing feedback that eventually results in market saturation. The supply chain for the new technology also influences these demand-side dynamics. If buyer interest and new orders exceed the sales rate the available inventory can support, adoption is limited to the number of units available. Dealers also manage their inventory levels by offering incentives to encourage consumers to buy the new technology when inventory is excessive, and raising prices when inventories are low.

The application of the aggregation model to the case of the diffusion of the Toyota Prius in the US demonstrates the importance of familiarity and supply constraints in new product diffusion (Keith 2012). First, supply constraints can have a significant impact on new product diffusion, limiting consumer adoption and explaining the existence of waiting lists. Second, consumers accumulate familiarity from exposure to marketing and word-of-mouth, explaining growing consumer adoption of the Toyota Prius over the past decade. Availability and familiarity interact, since low availability limits the growth of the installed base and thus the strength of the positive feedbacks created by word of mouth and social exposure. However, while the aggregate model effectively explains the aggregate adoption trend observed, it cannot explain the observed geographic clustering of adoption, motivating the development of a spatial model. Here I disaggregate the US population into $x$ geographic regions, incorporate the demographic attributes of those regions into the consumer choice formulation, and represent the spatial generation of information about the new technology among those regions, conceptualized in Figure 5. The model is formulated as a system of non-linear differential equations, solved by simulation.
5.1. Consumer Choice

As in the aggregate model, consumers choose the type of vehicle they will purchase based on the observable attributes of the available alternatives. The share of consumers currently using technology $i$ who choose to adopt technology $j$, $\sigma_{ij}$, is given by:

$$\sigma_{ij} = \frac{e^{u_{ij}}}{\sum_j e^{u_{ij}}}$$  \hspace{1cm} (1)$$

where $u_{ij}$ is the expected utility of technology $j$ as perceived by drivers of technology $i$ in region $x$. Here the perceived utility of a technology depends on both the utility of that technology and the extent to which a customer in region $x$ is familiar with that technology:

$$u_{ij}^e = u_{ij} \times F_{ij}$$  \hspace{1cm} (2)$$
where $F_{ijx}$ is the level of familiarity that adopters of technology $i$ in region $x$ have with technology $j$. The utility of technology $j$ for adopters of technology $i$ in region $x$, $u_{ijx}$, is a function of the observable attributes of the technology and demographic attributes of the consumer:

$$u_{ijx} = \sum_k \beta_k \chi_{ijkx} + \epsilon_{ijx}$$  \hspace{1cm} (3)

where $\beta_k$ represents the preference of consumers for attribute $k$, $\chi_{ijkx}$ is a matrix of observed attributes $k$ for adopters of technology $i$ considering technology $j$ in region $x$, and $\epsilon_{ijx}$ represents unobserved attributes and idiosyncratic consumer preferences that adopters of technology $i$ hold for technology $j$. In this model, the logit choice structure controls for potential sources of market heterogeneity, reflected in the predicted market share of the technology $j$ in region $x$.

5.2. Spatial Dynamics

To simulate the effect that drivers in region 'y' have on the propensity of consumers in region 'x' to adopt technology $j$, I simulate the process of socialization to technology $j$ both within and between regions. The socialization of consumers in region $x$ is the sum of marketing exposure and word-of-mouth occurring within region $x$ plus the word-of-mouth received from regions other than region $x$:

$$socialization_x = within\_region_x + from\_other\_regions_x$$  \hspace{1cm} (4)

Within-region socialization results from marketing, both national and regional, and from word-of-mouth from adopters of technology $j$, the factors found to be significant in the aggregate model:

$$within\_region_{j,x} = \alpha_n m_{j,n} + \alpha_r m_{j,r} + e_j \left( \frac{N_{j,s}}{N_s} \right)$$  \hspace{1cm} (5)

where $\alpha_n$ and $\alpha_r$ is the effectiveness of marketing spending for technology $j$ in national media outlets and regional media outlets respectively, $m_n$ is the amount spent marketing technology $j$ in national media outlets, $m_r$ is the amount spent marketing technology $j$ in region $x$ per quarter, $e_j$ is the effective contact rate with adopters of technology $j$ within region $x$, and $N_{j,s}$ is the number of
adopters of technology $j$ in region $x$. Although it is possible that consumers have a region-specific propensity to respond to advertising, there is no evidence for this, so I assume all consumers are influenced equally by a given level of marketing exposure ($\alpha_s$ and $\alpha_r$ are not indexed by region).

The word-of-mouth that is generated from region $y$ to region $x$ is a function of the fraction of adopters of technology $j$ in region $y$, and the strength of the social network ties between region $y$ and region $x$. Here the strength of ties represents the rate of information generated between regions across multiple communications channels, including in-person contacts, telephone calls and social network interactions. Because the actual network structure that has governed the spatial generation of information about technology $j$ may not known, I provide three alternative formulations for this spatial information generation, spanning a range of network topologies. Each network topology is tested to reveal how effectively each formulation explains the observed spatio-temporal adoption dynamics.

The first formulation, denoted the 'Mean Field' model, assumes all out-of-region adopters of technology $j$ are equally influential, regardless of location. The second formulation, the 'Island' model, assumes that no social influence occurs between regions, so each region is a diffusion island. The third formulation, the 'Radiation' model, is a more sophisticated network that mimics fluxes observed in real world transportation, migration and communications patterns (Simini, Gonzalez et al. 2012). In the Radiation model, the volume of social contact relevant to the choice of vehicle generated in region $y$ and affecting region $x$ increases with larger populations in regions $y$ and $x$, $P_y$ and $P_x$, and decreases with increases in other populations that exist within a ring of radius $r_{xy}$ centered on region $x$, $Q_{xy}$. The authors developed this model in response to the widely used 'gravity' model, which has multiple calibration parameters, making its use challenging in applications where previous data isn't available. The authors demonstrate that the radiation model predicts a network that is in good agreement with commuting, migration and communications patterns observed in the real world, and is parameter free. The three models I present here provide a good approximation of the spectrum of network topologies possible. The Mean Field and Island models are both extremes, which the Radiation model is a more complex and realistic intermediate model that captures real-world heterogeneity in cross-region word-of-mouth.
### Table 8: Spatial Social Influence Formulations

<table>
<thead>
<tr>
<th>Model</th>
<th>Out-of-Region Social Influence Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Field Model</td>
<td>[ I_{nj} = \frac{\sum_{y \neq x} N_{j,y}}{\sum_{y \neq x} N_y} ]</td>
</tr>
<tr>
<td></td>
<td>where ( \hat{e}_j ) is the effective contact rate with Prius drivers in all other regions ( y \neq x ).</td>
</tr>
<tr>
<td>Island Model</td>
<td>[ I_{nj} = 0 ]</td>
</tr>
<tr>
<td>Radiation Model</td>
<td>[ I_{nj} = \frac{\sum_{y \neq x} \left( \frac{N_{j,y}}{N_y} \right)}{P_x} ]</td>
</tr>
<tr>
<td></td>
<td>where the Radiation network communication generation from region ( y ) to region ( x ), ( \phi_{j,y,x} ), is given by:</td>
</tr>
<tr>
<td></td>
<td>[ \phi_{j,y,x} = \frac{P_x P_y}{(P_x + Q_{xy})(P_x + P_y + Q_{xy})} ]</td>
</tr>
<tr>
<td></td>
<td>where ( P_x ) is the population in region ( x ), ( P_y ) is the population in region ( y ), and ( Q_{xy} ) is the population within the ring centered at region ( x ) with radius ( r_{xy} ), excluding ( P_x ) and ( P_y ).</td>
</tr>
</tbody>
</table>

### 4. Model Estimation

To estimate model parameters for the case of the spatio-temporal diffusion of the Prius, I elaborate on the generic model above. As in Essay 1, I assume consumers choose between the Prius and a comparable gasoline vehicle within an individual market segment. To operationalize the sources of market heterogeneity described in Section 2, I define the attributes of consumer choice shown in Table 2:
Table 9: Definition of Consumer Choice Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price / ln(Income)</td>
<td>Vehicle effective purchase price (MSRP less incentives) in thousands of dollars, divided by the natural log of median household income in thousands of dollars.</td>
</tr>
<tr>
<td>Operating Cost</td>
<td>Cost of gasoline in cents per mile, calculated using combined mpg (55%/45% city/highway split).</td>
</tr>
<tr>
<td>Greenhouse Gas Emissions</td>
<td>Tailpipe greenhouse gas emissions as a fraction of emissions from the comparable gasoline vehicle.</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>Percentage of population age 25 or over with a college degree or higher.</td>
</tr>
<tr>
<td>Green Preference</td>
<td>Fraction of the population who are registered Green Party voters.</td>
</tr>
<tr>
<td>Dealerships</td>
<td>Number of dealerships in region x.</td>
</tr>
<tr>
<td>Dealership Distance</td>
<td>Distance in miles to the nearest region containing a Toyota dealership. 0 if region contains a Toyota dealership.</td>
</tr>
<tr>
<td>Annual VMT</td>
<td>Annual miles travelled per vehicle, in thousands of miles.</td>
</tr>
<tr>
<td>Constant for Gasoline</td>
<td>1 for conventional gasoline vehicle, 0 for Prius.</td>
</tr>
</tbody>
</table>

My analysis builds on the observation that Prius adoption clustering occurs at both the regional and local levels in the United States. First, I analyze regional clustering across the United States using Metropolitan Statistical Areas (MSAs) as the geographic unit of analysis. Second, I analyze local clustering within a single region, the San Francisco Bay Area, using zip codes as the geographic unit of analysis.

5. Results

5.1. Analysis of Regional Clustering

To analyze regional clustering patterns at the US national level, I specify the model to represent all 331 MSAs\(^2\) in the United States, as defined by the US Office of Management and Budget. MSAs are regions with high population density and economic activity, representing

\(^2\) In total, 366 MSAs are defined in the US. However, major cities have both a Consolidated MSA (CMSA) code (such as 2162 for Detroit-Ann Arbor-Flint), and Primary MSA (PMSA) codes for the sub-regions (0440 for Ann Arbor, 2160 for Detroit, 2640 for Flint). Removing redundant 'alternative codes' and CMSAs leaves \(n = 331\) MSAs for this analysis.
approximately 75% of the US population, and 89% of US Prius sales, despite only covering a modest fraction of the US by area (Figure 23).

**Figure 23: US Metropolitan Statistical Areas (Bright Green)**

[Image: Map of US Metropolitan Statistical Areas with MSAs highlighted in bright green.]

Source: (ESRI 2007)

The majority of MSAs have a population of less than 400,000 people, although a number of much larger MSAs exist, including Los Angeles-Long Beach, Chicago and New York City. The demographics of the average MSA are shown in Table 2, which are largely consistent with US population averages. Interestingly, the coefficient of variation in Prius sales by region is considerably greater than the coefficient of variation in the demographic variables.
In this model, the demand-side of the market is disaggregated to represent each MSA. However, because allocations of the Prius to individual dealers are not available, it is not possible to estimate the supply of vehicles at the dealer level (and by extension, the ZIP code or MSA). Because the results of Essay 1 emphasize the importance of capturing supply constraints when estimating model parameters, I use a Mean Field approximation to the waitlist, with uniform vehicle availability across all regions. This approach is reasonable given the expectation that Toyota
allocates Prius inventory to dealerships in proportion with customer demand. I assume the dealer incentive to be exogenous based on the historic incentives observed, and calibrate Prius sales ($s_{p,x,t}$) against a new dataset called Customer Demand, $\xi_{p,x,t}$, that captures both the Sales and Waiting Lists observed in the market. Customer Demand is calculated as the observed rate of Prius sales in region $x$ at time $t$, adjusted for the observed change in Prius waiting list from time $t-1$ to time $t$:

$$\xi_{p,x,t} = s_{p,x,t} + s_{p,x,t}(W_{p,t} - W_{p,t-1})$$

(10)

where $s_{p,x,t}$ is the rate of Prius sales in region $x$ at time $t$, and $W_{p,t}$ is the Prius waiting list at time $t$.

### Table 11: Discrete Choice Parameters - Regional Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Mean Field Model</th>
<th>Island Model</th>
<th>Radiation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant for Gasoline Vehicle</td>
<td>dmnl</td>
<td>-0.255 (-1.131, 0.396)</td>
<td>-0.465 (-1.907, 0.704)</td>
<td>-0.526 (-1.621, 0.129)</td>
</tr>
<tr>
<td>Purchase Price / ln(Income)</td>
<td>dmnl/($'000/ln($'000))</td>
<td>-0.086 (-0.539, 0.250)</td>
<td>-0.130 (-0.782, 0.216)</td>
<td>-0.123 (-0.728, 0.091)</td>
</tr>
<tr>
<td>Operating Cost</td>
<td>dmnl/(cents/mile)</td>
<td>-0.242*** (-0.24, -0.033)</td>
<td>-0.237*** (-0.248, -0.09)</td>
<td>-0.235*** (-0.221, -0.08)</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>dmnl/(% over 25 with B. deg.)</td>
<td>-0.646*** (-1.68, -0.207)</td>
<td>-0.447 (-1.263, 0.397)</td>
<td>-0.475 (-1.298, 0.289)</td>
</tr>
<tr>
<td>Political Preference</td>
<td>dmnl/(% Dem. Presid. voters)</td>
<td>0.063 (-0.389, 0.648)</td>
<td>0.126 (-0.299, 0.749)</td>
<td>0.155 (-0.288, 0.621)</td>
</tr>
<tr>
<td>Dealerships</td>
<td>dmnl/(# dealerships)</td>
<td>-0.010*** (-0.02, -0.005)</td>
<td>-0.009*** (-0.02, -0.003)</td>
<td>-0.009*** (-0.015, -2E-4)</td>
</tr>
<tr>
<td>VMT</td>
<td>dmnl/(miles/year)</td>
<td>0.039*** (0.010, 0.069)</td>
<td>0.027 (-0.002, 0.057)</td>
<td>0.025*** (0.002, 0.045)</td>
</tr>
</tbody>
</table>

(lower, upper) = 95% confidence interval. *** = significant at $p = 0.01$. ** = significant at $p = 0.05$. * = significant at $p = 0.1$. 

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Table 12: Socialization Parameters - Regional Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean Field Model</th>
<th>Island Model</th>
<th>Radiation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective Contact Rate – In-Region Prius Drivers</td>
<td>13.143***</td>
<td>12.714***</td>
<td>12.052***</td>
</tr>
<tr>
<td></td>
<td>(8.721, 33.061)</td>
<td>(6.062, 29.69)</td>
<td>(9.51, 26.56)</td>
</tr>
<tr>
<td>Effective Contact Rate – Mean Field Out-of-region Prius Drivers</td>
<td>-1.634</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(-4.93, -0.753)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Effective Contact Rate – Radiation Out-of-region Prius Drivers</td>
<td>-</td>
<td>-</td>
<td>7.233</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
<td>(-1.2E3, 10E3)</td>
</tr>
<tr>
<td>Effectiveness of National Marketing</td>
<td>0.0003***</td>
<td>0.0002***</td>
<td>0.0002***</td>
</tr>
<tr>
<td></td>
<td>(1E-4, 5E-4)</td>
<td>(4E-5, 3E-3)</td>
<td>(1E-4, 3E-4)</td>
</tr>
<tr>
<td>Effectiveness of State Marketing</td>
<td>0.016***</td>
<td>0.016***</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.003, 0.033)</td>
<td>(0.004, 0.044)</td>
<td>(5E-3, 0.026)</td>
</tr>
<tr>
<td>Av. Socialization from In-Region Prius Drivers</td>
<td>74%</td>
<td>88%</td>
<td>87%</td>
</tr>
<tr>
<td>Av. Socialization from Out-of-Region Prius Drivers</td>
<td>13%^</td>
<td>-</td>
<td>&lt;1%</td>
</tr>
<tr>
<td>Av. Socialization from National Marketing</td>
<td>13%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td>Av. Socialization from State Marketing</td>
<td>&lt;1%</td>
<td>&lt;1%</td>
<td>&lt;1%</td>
</tr>
</tbody>
</table>

^ = negative social influence

Table 13: Goodness of Fit Statistics - Regional Model

<table>
<thead>
<tr>
<th>Payoff</th>
<th>-7.38E+07</th>
<th>-7.44E+07</th>
<th>-7.38E+07</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean R² – Sales</td>
<td>0.737</td>
<td>0.735</td>
<td>0.735</td>
</tr>
<tr>
<td>Mean MAPE – Sales</td>
<td>0.681</td>
<td>0.783</td>
<td>0.769</td>
</tr>
<tr>
<td>Mean Theil Bias Fraction (U_m) – Sales</td>
<td>0.084</td>
<td>0.078</td>
<td>0.080</td>
</tr>
<tr>
<td>Mean Theil Unequal Variance Fraction (U_v) – Sales</td>
<td>0.165</td>
<td>0.122</td>
<td>0.124</td>
</tr>
<tr>
<td>Mean Theil Unequal Covariance Fraction (U_c) – Sales</td>
<td>0.750</td>
<td>0.800</td>
<td>0.796</td>
</tr>
</tbody>
</table>

Parameter estimates for these models are shown in Table 3, with summary statistics shown in Tables 4 and 5. At the US MSA level, these models provide modest support for the a priori market heterogeneity hypotheses for adoption clustering provided in Section 2. The results indicate that the Prius is more attractive in markets that have lower effective purchase prices (MSRP less incentives), higher vehicle operating costs, a higher percentage of Democrat voters and where drivers cover greater mileages annually, although the purchase price and political preference coefficients are not statistically significant. The lack of statistical significance on the purchase price coefficient is surprising. However, the purchase price of the Prius and the
comparable gasoline vehicle vary relatively little over in this sample data, which makes parameter estimation more difficult. These results do not support a-priori expectations regarding vehicle greenhouse gas emissions, educational attainment levels and proximity to Toyota dealerships. I expected that the Prius would be more attractive because it produces fewer greenhouse gas emissions than the conventional gasoline alternative, revealed in a negative coefficient for greenhouse gas emissions. The finding here suggests that consumers prefer vehicles that pollute more, all else being equal. One possible explanation for this result is that greenhouse gas emissions are highly correlated with vehicle attributes not captured in this model, such as acceleration, top speed, comfort and features, an effect discussed previously by Brownstone, Bunch et al. (2000). I expected that the Prius would be more attractive in regions with a more highly educated population that better understands the costs and benefits of this complex technology. Finally, I expected that the Prius would be more attractive in regions with more Toyota dealerships, because car buyers would have a lower search cost to find, test and purchase a Prius, but this was not revealed in the results.

Complementing the market heterogeneity effects, these results suggest that social contagion played an important role in the spatial diffusion dynamics observed. Consistent with prior research on aggregate Prius adoption in the United States, consumer familiarity with the Prius accumulates from both word-of-mouth and marketing. The breakdown of socialization by source is telling. In each model, word-of-mouth from Prius drivers within each MSA is very important, contributing over 70% of total socialization to consumers in that MSA. In contrast, these results provide little evidence for the importance of word-of-mouth between regions at the MSA level, because in both the Mean Field and Radiation models, the out-of-region word-of-mouth term is statistically insignificant. In each model, Toyota's marketing efforts at both the national and state levels make a meaningful contribution to consumer familiarity with the Prius. National marketing contributes more to the socialization process due to Toyota's greater marketing spending in national media, even though the larger coefficient for marketing spending in regional markets than in national markets reflects the greater expense of marketing in national media outlets that reach all regional markets.

Overall, these models provide positive if not conclusive evidence to explain the patterns of Prius adoption clustering observed at the regional level. Differences in Prius adoption rates are explained by multiple sources of market heterogeneity. Social contagion is shown to be important, but mainly within rather than between MSAs, suggesting that the longer ties that exist between metropolitan regions within the US have limited influence over the diffusion of the Prius. This result
is consistent with the interpretation of hybrid vehicle diffusion as a complex contagion, where consumers require repeated firsthand experiences such as observing hybrid vehicles in use and riding in hybrid taxis to develop the familiarity that leads to the decision to adopt. These contagion dynamics suggest that adoption clustering at the national level results primarily from market heterogeneity, because the effect of social network ties between regions is minimal. This makes sense, because distant informants send a much weaker message than seeing, touching and driving the Prius. In the following section I apply this model at the local level to explain the existence of adoption clustering within individual metropolitan regions.

5.2. Analysis of Local Clustering

To analysis Prius adoption clustering at the local level, I concentrate on the San Francisco Bay Area. Selected as North America’s Greenest City (Economist Intelligence Unit 2011), it is not surprising that the Prius has achieved strong sales in this region. Here I specify the model to represent each of the 270 ZIP code regions shown in Figure 9. A histogram of population by ZIP code (Figure 10) shows that while many ZIP codes have fewer than 2,000 residents, often in rural areas such as Marin county, the majority of Bay Area ZIP codes have between 6,000 and 46,000 residents.

**Figure 25: San Francisco Bay Area ZIP Codes**
The demographic attributes of the populations in the Bay Area ZIP codes, shown in Table 6, vary considerably from the national average. Compared with the attributes of the population of US MSAs, it can be seen that Bay Area residents have considerably higher incomes and education levels than the national average, and exhibit stronger preferences for environmental stewardship, to the extent these are captured by Green Party membership. Not surprisingly, per capita Prius sales in the Bay Area are more than five times greater than the average across other US MSAs. As at the MSA level, the coefficient of variation is much large for sales than for the demographic attributes shown, suggesting positive feedback may be amplifying initial heterogeneities.

**Table 14: Bay Area ZIP Code Population Attributes**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Household Income ($/year)</td>
<td>$65,200</td>
<td>$24,800</td>
</tr>
<tr>
<td>Political Preference (% Green Party members)</td>
<td>1.3%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Educational Attainment (% 25 or over with College Degree or higher)</td>
<td>46.5%</td>
<td>18.0%</td>
</tr>
<tr>
<td>10-year Cumulative Prius Sales per Capita</td>
<td>0.016</td>
<td>0.016</td>
</tr>
</tbody>
</table>
As in the regional analysis, I use non-linear least squares regression to estimate this model for the
diffusion of the Prius in the Bay Area, with minimal changes in model specification. Because not
every Bay Area ZIP code contains a Toyota dealership, I capture dealership access as the distance to
the nearest ZIP code containing a Toyota dealership, with the expectation that the Prius becomes
less attractive as the distance to the nearest dealership increases. Also, I use Green Party
membership as a proxy for environmental preferences, capturing this concept more explicitly than
Democratic party voting patterns. Two changes exist in the socialization structure. I combine
national and state marketing into a single variable, because all consumers in the Bay Area are
exposed to the same regional marketing, but I include a third word-of-mouth variable to capture
the influence of all US Prius drivers outside the Bay Area, using a Mean Field formulation, as shown
in Table 1, for computational tractability. Parameter estimates for the three alternative models are
shown in Table 7, with summary statistics in Table 8 and Table 9:

Table 15: Discrete Choice Coefficients - Local Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Units</th>
<th>Mean Field Model</th>
<th>Island Model</th>
<th>Radiation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant for Conventional Gasoline Vehicle</td>
<td>3.654***</td>
<td>dmnl</td>
<td>4.655***</td>
<td>4.420***</td>
<td></td>
</tr>
<tr>
<td>Vehicle</td>
<td></td>
<td>(2.02, 4.72)</td>
<td>(3.33, 6.17)</td>
<td>(2.94, 5.01)</td>
<td></td>
</tr>
<tr>
<td>Purchase Price / ln(Income)</td>
<td>-0.391</td>
<td>dmnl/($000/ln($000))</td>
<td>-0.233</td>
<td>-0.143</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.14, 0.36)</td>
<td>(-1.23, 0.44)</td>
<td>(-0.73, 0.30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating Cost</td>
<td>-0.606***</td>
<td>dmnl/ (cents/mile)</td>
<td>-0.599***</td>
<td>-0.666***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.62, -0.31)</td>
<td>(-0.75, -0.50)</td>
<td>(-0.66, -0.38)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Greenhouse Gas Emissions</td>
<td>2.891</td>
<td>dmnl/(% gas veh. emissions)</td>
<td>1.173</td>
<td>2.432</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.58, 4.43)</td>
<td>(-0.76, 3.21)</td>
<td>(-1.01, 2.86)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>2.162***</td>
<td>dmnl/ (% over 25 with B. deg.)</td>
<td>1.951***</td>
<td>1.753***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.30, 2.80)</td>
<td>(1.14, 2.77)</td>
<td>(1.16, 2.09)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Political Preference</td>
<td>0.388***</td>
<td>dmnl/ (% green party members)</td>
<td>0.387***</td>
<td>0.349***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.29, 0.46)</td>
<td>(0.33, 0.45)</td>
<td>(0.25, 0.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dealership Distance</td>
<td>-0.011</td>
<td>dmnl/(miles to dealership)</td>
<td>-0.029*</td>
<td>0.021***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.03, 0.01)</td>
<td>(-0.09, 0.00)</td>
<td>(0.01, 0.03)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VMT</td>
<td>0.012***</td>
<td>dmnl/ (miles/year)</td>
<td>0.019***</td>
<td>0.021***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004, 0.018)</td>
<td>(0.01, 0.03)</td>
<td>(0.02, 0.02)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(lower, upper) = 95% confidence interval. *** = significant at p = 0.01. ** = significant at p = 0.05. * = significant at p = 0.1.
Table 16: Socialization Parameters - Local Model

<table>
<thead>
<tr>
<th>Variable Coefficient</th>
<th>Mean Field Model</th>
<th>Island Model</th>
<th>Radiation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective Contact Rate – In-Region Prius Drivers</td>
<td>9.995** (0.93, 61.86)</td>
<td>58.468*** (31.31, 87.14)</td>
<td>5.112 (-11.83, 31.98)</td>
</tr>
<tr>
<td>Effective Contact Rate – Mean Field Out-of-region Prius Drivers</td>
<td>7.697 (-164.9, 68.14)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Effective Contact Rate – Radiation Network Out-of-region Prius Drivers</td>
<td>-</td>
<td>-</td>
<td>56.163*** (25.29, 88.07)</td>
</tr>
<tr>
<td>Effective Contact Rate – Non-Bay Area Prius Drivers</td>
<td>25.480 (-270.4, 670.8)</td>
<td>-</td>
<td>-84.913* (-195.9, 3.95)</td>
</tr>
<tr>
<td>Effectiveness of Marketing (National + State)</td>
<td>0.006*** (0.00, 0.02)</td>
<td>0.007*** (0.00, 0.02)</td>
<td>0.009*** (0.00, 0.01)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable Coefficient</th>
<th>Mean Field Model</th>
<th>Island Model</th>
<th>Radiation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Av. Socialization from In-ZIP Prius Drivers</td>
<td>34%</td>
<td>82%</td>
<td>6%</td>
</tr>
<tr>
<td>Av. Socialization from Out-of-ZIP Prius Drivers (Mean Field)</td>
<td>23%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Av. Socialization from Out-of-ZIP Prius Drivers (Radiation)</td>
<td>-</td>
<td>-</td>
<td>60%</td>
</tr>
<tr>
<td>Av. Socialization from Non-Bay Area Prius Drivers</td>
<td>17%</td>
<td>-</td>
<td>20%^</td>
</tr>
<tr>
<td>Av. Socialization from Marketing</td>
<td>26%</td>
<td>18%</td>
<td>14%</td>
</tr>
</tbody>
</table>

^ = negative social influence

Table 17: Goodness of Fit Statistics - Local Model

<table>
<thead>
<tr>
<th>Payoff</th>
<th>-647294</th>
<th>-664433</th>
<th>-614924</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean R² – Sales</td>
<td>0.518</td>
<td>0.512</td>
<td>0.513</td>
</tr>
<tr>
<td>Mean MAPE – Sales</td>
<td>1.308</td>
<td>1.724</td>
<td>1.006</td>
</tr>
<tr>
<td>Mean Theil Bias Fraction (Um) – Sales</td>
<td>0.102</td>
<td>0.102</td>
<td>0.101</td>
</tr>
<tr>
<td>Mean Theil Unequal Variance Fraction (Us) – Sales</td>
<td>0.217</td>
<td>0.236</td>
<td>0.199</td>
</tr>
<tr>
<td>Mean Theil Unequal Covariance Fraction (Uc) - Sales</td>
<td>0.681</td>
<td>0.662</td>
<td>0.700</td>
</tr>
</tbody>
</table>

The Bay Area models provide stronger evidence in support of both the market heterogeneity and social contagion explanations for adoption clustering. In each model, vehicle utility increases with lower purchase prices and operating costs as expected, providing support for hybrid vehicle incentives that reduce the incremental purchase price associated with hybrid vehicle adoption. Prius utility increases in ZIP codes with higher levels of education, stronger environmental preferences and where greater driving distances providing a better return on
improved fuel economy, also as expected. As in the regional models, greenhouse gas emissions take a positive valence, contrary to expectations, which may be explained by the unobserved attributes of the gasoline vehicle. However, these models give mixed signals about the effect of proximity to a Toyota dealership. Whereas the Mean Field and Island models take a negative valence on distance to a Toyota dealership as expected, the Radiation model dealership coefficient has a positive coefficient and is statistically significant.

Patterns of social influence in the Bay Area models are more distinct also. Toyota's marketing spending through national and state channels is an important source of information, providing between 14% and 26% of consumers' socialization to the Prius, varying with different social network topologies. However, obvious differences in the apportionment of socialization from word-of-mouth exist once I introduce different Prius driver populations. In the Island model, where no inter-region network ties exist, 82% of socialization comes from within-region word-of-mouth, broadly consistent with Island regional model, noting that the region here is an individual ZIP code. In the Mean Field model, 34% of socialization comes from word-of-mouth within the local ZIP code, which is quite large given the smaller population of an individual ZIP code, while 23% of socialization comes from other Prius drivers within the Bay Area, and 17% of socialization from all other Prius drivers in the United States outside the Bay Area. These results suggest local interactions are be important, providing more socialization than interactions with the numerous individuals from all other parts of the country. The Radiation model is even more pronounced. Only 6% of socialization coming from word-of-mouth within the local ZIP code, but 60% comes from word-of-mouth from other ZIP codes in the Bay Area (where interactions are weighted according to the Radiation network), and 20% from all other Prius drivers outside the Bay Area. However, given the relative population of each category, individuals within the local ZIP code are most influential. The existence of negative word-of-mouth from non-Bay Area Prius drivers in the Radiation model is puzzling, but only weakly statistically significant. Do car buyers in the Bay Area really become less familiar with the Prius as consumer adoption of the Prius outside the Bay Area grows? This seems unlikely, but could be rationalized post-hoc as evidence of dissociative influence (White and Dahl 2007), as growth in Prius adoption elsewhere leads Bay Area car buyers to shy away from the Prius, because widespread adoption of this once unique innovation now provides consumers less identity differentiation.

Spatial analysis of Prius diffusion at different levels of aggregation highlights the nature of social interactions that have been influential in the diffusion of the Prius. The regional-level analysis concludes that little social influence exists between metropolitan regions, suggesting that
long but weak ties such as Facebook connections do little to build consumer familiarity with the Prius. The local-level analysis supports this, concluding that substantial social influence occurs within a consumer's home ZIP code and in the surrounding metropolitan region, consistent in-person discussions, observations of Prius vehicles in use and opportunities to experience the Prius firsthand. The importance of these close ties suggests a complex contagion where reinforcement from multiple sources is an essential element of the diffusion process, not surprising given the expensive, complex and durable nature of the Prius. Both levels of analysis suggest that long-range tie have relatively little impact on the diffusion process. Whereas the regional models reveal US car buyers' average Prius familiarity to be in the range 13-25% (of full acceptance and inclusion of the Prius in their consideration set), the local models reveal Bay Area car buyers' average Prius familiarity to be much greater, in the range 79-89%. The higher density of Prius vehicles in the Bay Area leads to more frequent interactions that build consumer familiarity, leading to more Prius purchases and yet more frequent interactions, a reinforcing feedback.

Finally, I consider the contribution that the behaviorally oriented diffusion structure and the utility oriented discrete choice structure make respectively to explaining the variation observed in the data. Here I develop four additional models. First, in the Full Familiarity model, I assume all consumers have full familiarity with the Prius, so all variation is explained by the discrete choice coefficients, the classic utility-maximizing case. Second, I estimate each of the Mean Field, Island and Radiation models with Constant Utility, where each of the discrete choice elements takes its average value over time (both not geographically) from the data, such that it estimates a constant market share for the Prius within each region. In these models, all variation simulated by the model is driven by the accumulation of consumer familiarity from marketing and word-of-mouth. Estimating parameters for these models from the Prius case (Table 18) highlights the relative ability of these modeling approaches to explaining the diffusion dynamics observed. The Full Familiarity model implies the gasoline vehicle is vastly superior to the Prius, reflected in a strongly positive coefficient on the gasoline vehicle constant, needed to explain low Prius adoption in the absence of consumer familiarity dynamics. In contrast, each of the Constant Utility models captures very little of the variation in the data (low R² values), because while explaining the overall dynamics of consumer familiarity accumulation, these models do not capture short-term fluctuations in response to gasoline prices, government incentives and other sources of market heterogeneity.
Table 18: Local Model Parameters – Constant Familiarity and Constant Utility

<table>
<thead>
<tr>
<th>Variable Coefficient</th>
<th>Full Familiarity</th>
<th>Constant Utility (Mean Field)</th>
<th>Constant Utility (Island)</th>
<th>Constant Utility (Radiation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective Contact Rate – In-Region Prius Drivers</td>
<td>-</td>
<td>29.286</td>
<td>157.801</td>
<td>5.112</td>
</tr>
<tr>
<td>Effective Contact Rate – Out-of-region Prius Drivers</td>
<td>-</td>
<td>-1540.87</td>
<td>-</td>
<td>56.163</td>
</tr>
<tr>
<td>Effective Contact Rate – Non-Bay Area Prius Drivers</td>
<td>-</td>
<td>4540.8</td>
<td>-</td>
<td>-84.473</td>
</tr>
<tr>
<td>Effectiveness of Marketing (National + State)</td>
<td>-</td>
<td>0.0017</td>
<td>0.0039</td>
<td>0.0088</td>
</tr>
<tr>
<td>Constant for Conventional Gasoline Vehicle</td>
<td>10.600</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Purchase Price / ln(Income)</td>
<td>-0.594</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Operating Cost</td>
<td>-0.692</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Greenhouse Gas Emissions</td>
<td>-7.835</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>4.420</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Political Preference</td>
<td>0.646</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Dealership Distance</td>
<td>0.024</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>VMT</td>
<td>0.009</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 19: Goodness of Fit Statistics - Constant Familiarity and Constant Utility

<table>
<thead>
<tr>
<th>Payoff</th>
<th>-758813</th>
<th>-8.99E06</th>
<th>-5.21E06</th>
<th>-5.37E06</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean R² – Sales</td>
<td>0.491</td>
<td>0.043</td>
<td>0.043</td>
<td>0.043</td>
</tr>
<tr>
<td>Mean MAPE – Sales</td>
<td>2.743</td>
<td>0.799</td>
<td>1.094</td>
<td>0.784</td>
</tr>
<tr>
<td>Mean Theil Bias Fraction (Um) – Sales</td>
<td>0.193</td>
<td>0.251</td>
<td>0.121</td>
<td>0.180</td>
</tr>
<tr>
<td>Mean Theil Unequal Variance Fraction (Us) – Sales</td>
<td>0.277</td>
<td>0.255</td>
<td>0.406</td>
<td>0.291</td>
</tr>
<tr>
<td>Mean Theil Unequal Covariance Fraction (Uc) - Sales</td>
<td>0.530</td>
<td>0.494</td>
<td>0.472</td>
<td>0.529</td>
</tr>
</tbody>
</table>

6. Discussion

Despite the extensive literature on the diffusion of durable goods, and the spatial diffusion of non-durable innovations, relatively little research informs how durable goods such as new automotive technologies diffuse spatially (Mahajan and Peterson 1979; Redmond 1994). I propose social contagion and market heterogeneity as potential causes of the Prius adoption clustering.
observed, developing a model that captures social contagion both within and between regional populations, and regional heterogeneity in consumer Prius adoption thresholds. I find that social contagion plays a critical role in the patterns of adoption observed, but focused at the local level, where first-hand experiences provide opportunities to learn about the complex innovation. This positive feedback accentuates heterogeneous market thresholds held by consumers in different markets, further reinforced by the strategic investment of marketing efforts in regional markets with high early adoption. Below I discuss theoretical and managerial implications of my findings, and opportunities for further research in this area.

6.1. Theoretical Implications

The model developed here contributes to the literature on spatial innovation diffusion, distinguishing between social contagion dynamics and heterogeneity in consumers' adoption threshold, complementing the work of Toole, Cha et al. (2012) who explore the spatial diffusion of Twitter. In the absence of prior research on the topology of social influence in the diffusion of durable goods, the result here provides some evidence about the appropriate unit of analysis for spatial diffusion studies. I find evidence of spatial social contagion between ZIP codes in a single metropolitan region, but not between metropolitan regions at the national level. The everyday commuting patterns of urban drivers and the action radius of vehicle explain how firsthand interactions occur routinely between drivers from different ZIP codes within a single metropolitan region, but not between regions. However, these social contagion dynamics are not sufficient to explain the patterns of adoption observed, without the existence of heterogeneous adoption thresholds in different regions. Thus, capturing technological and demographic decision influences is also important. Here, I use a logit model to represent consumer choice between alternatives, capturing the multi-attribute nature of the product being considered.

The performance of the regional and local models provide ideas about how to model spatial diffusion dynamics efficiently. When modeling a single region such as the San Francisco Bay Area, it may not be necessary to model the influence of other regions in the same detail, instead apply a simplification such as the mean field used here. In the regional model, the Mean Field and Radiation network topologies made only modest improvements over the Island model, suggesting that the island assumption may be sufficiently accurate at the national level. It is interesting to consider how these dynamics might change for innovations other than automotive technologies. Rogers (2003) argues that the rate of adoption of an innovation will increase as that innovation provides greater relative utility, greater compatibility with existing systems and norms, relatively
less complexity, is readily observable in use and can be easily trialed. While relatively better technologies should naturally lead to faster diffusion spatially as in aggregate, observability may be the most significant barrier for durable goods in the spatial context. Unlike digital innovations such as Twitter, the benefits of new household appliances, game consoles, sporting equipment and vehicles are difficult to effectively communicate through distant social network ties, even when those innovations themselves are internet-enabled.

6.2. Managerial Implications

For vehicle manufacturers, my findings provide suggestions for effective marketing strategies to promote innovative vehicle technologies. Traditional advertising on television, radio and in print media plays an important role introducing new vehicles to consumers. However, the importance of first-hand contact with the new vehicle to build consumer familiarity provides a role for display vehicles at public events, extended test-drivers from dealerships, rental experiences, low-cost, flexible leases and other means to give consumers nontrivial experience with these vehicles. Building on the opportunity for reinforcement from trusted friends, early adopters of the platform may be the best salespeople of the new technology, harnessing the power of word-of-mouth. As a result, marketing effort and vehicle distribution should favor markets where an installed base of the new platform already exists.

For policymakers, the distinction between social contagion and market heterogeneity informs how effective incentives to encourage consumer adoption of hybrid and electric vehicles will be. Incentives will be most cost-effective in markets with high consumer familiarity with the new platform and with relatively lower adoption thresholds. Counter-intuitively, this is likely to be in markets where the platform has already achieved significant adoption, because the installed base of vehicles socializes consumers to the new platform. In markets with low prior adoption of the new platform, other efforts that build consumer familiarity may be more cost-effective initially, such as deployment of vehicles in government and taxi fleets. The model developed here provides a transparent and empirically grounded framework to explore the relative effectiveness of...

6.3. Limitations and Future Opportunities

Opportunities for future work include applying the spatial diffusion model to other geographic regions, including other countries, and to other durable technologies. Analyzing the diffusion of the Prius in markets less obviously green than the San Francisco Bay Area will add further insight to these findings. This model can also inform markets for other alternative fuel
vehicles such as plug-in electric vehicles. The ‘chicken-and-egg’ infrastructure dynamics so critical to the success of alternative fuel vehicles are not considered here (the market formation dilemma in which alternative fuel vehicles need widespread fueling infrastructure to be viable, and fuel providers need an installed base of vehicles to invest in infrastructure), because conventional hybrid-electric vehicles use the existing gasoline infrastructure. However, early adopters of hybrid-electric vehicles are likely to be early adopters of more radical electric vehicle technologies, as both technologies appeal to the same potential buyers, such as environmentalists and technophiles. Indeed, the Toyota Prius was the number one vehicle traded-in by early adopters of the GM Volt plug-in hybrid electric vehicle (Canny 2011), suggesting that clustering will also be observed in the plug-in electric vehicle market. Indeed, the positive feedback loop created by the strategic location of recharging infrastructure where people expect the most EVs to be sold will only accentuate clustering further. Simulating the diffusion of plug-in electric vehicles will inform the need for the installation of recharging infrastructure and evolution of the electricity grid, temporally and spatially.
References


Appendix A: Data Sources

A.1. Vehicle Sales
Quarterly sales data for individual hybrid vehicle models, total car sales and total light vehicle sales in each ZIP code was obtained from R.L.Polk, an automotive data provider, for the time period first quarter of 2001 to the second quarter of 2010 inclusive. For this analysis, sales in each ZIP code were aggregated to obtain quarterly sales by region. To estimate sales by region for the first two quarters after the Prius was launched, interpolation of the known national sales for this period was undertaken, based on sales achieved in quarter one 2001. Annual market shares by EPA Vehicle Class were obtained from Appendix F of the US EPA's report *Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2009* (EPA 2009).

A.2. Household Income
Household income by zip code for the year 2000 were obtained from the U.S. Census Bureau (2010).

A.3. Environmental Preferences
Numerous studies have identified consumers' preference for environmental protection as an important motivation for consumer adoption of hybrid-electric vehicles. Previous studies have used Green Party membership or Sierra Club membership as proxies for environmental preferences (Sims Gallagher and Muehlegger 2008; Heutel and Muehlegger 2009). Here we use the percentage of Democrat voters as a proxy for environmental stewardship preference, noting that Democrat voters express greater concern for the risk of climate change (Gallup 2008; Leiserowitz, Maibach et al. 2011). Presidential voting by county was obtained from the New York Times (New York Times 2008).

A.4. Gasoline Prices
Considerable variation in gas prices exists across the US (up to 60 cents/gallon), caused by differences including fuel taxes, environmental regulations and access to refineries and crude oil supplies. Retail gasoline prices by state were synthesized by combining the national average monthly gasoline price (EIA 2011) with cross-sectional gas prices by state in December 2011 (AAA 2011).

A.5. Government Incentives
Data describing government incentives for which the Prius is eligible were collated based on the Union of Concerned Scientists' list of hybrid vehicle incentives (UCS 2010). The details of state and local government incentives were gathered from numerous government departmental websites. These incentives take various forms, including tax credits, tax deductions, high-occupancy vehicle (HOV) lane access, exemption from emissions testing and discounted parking. Only financial incentives were included in this model. The value of tax deductions was estimated as 15% of the amount of the tax deduction, the marginal tax rate that has applied to the mean per capita income in the United States each year over the past decade.

A.6. Dealer Incentives
Incentives that influence the price of the Prius include cash rebates to customers, reduced rate financing and discounts to dealers. Weekly data describing the range of incentives being offered by Toyota for purchase of the Prius for the period 2003-2010 were obtained from the Automotive News Data Center. Monthly dealer incentive data was calculated by averaging weekly incentives offered for each month, using a net present value calculation to estimate the present value of reduced-rate financing to consumers. Data relating the level of dealer incentive offered to the length of time the vehicle had been in the dealer's inventory was obtained from JD Power's Power Information Network, a database of real-time transaction data obtained from across thousands of dealerships in the United States.

A.7. Prius Supply
The Prius has been manufactured exclusively in Japan for all global markets since its introduction. Prius export data from Japan to the United States was obtained from Fourin and Toyota. This data was available on an annual basis for 2000-2002, and a monthly basis for 2003-2010. For the period 2000-2002, monthly production and exports were estimated using linear interpolation.

A.8. Marketing Expenditure
Marketing expenditure data for the Prius was purchased from Kantar Media, a marketing intelligence provider. This data measures Toyota's monthly Prius marketing expenditure on radio, television, newspapers, magazines and the Internet in the United States.

A.9. Vehicle Specifications
Specifications of the Prius and comparable vehicles such as Toyota’s Corolla and Matrix models by Model Year were obtained from a consumer automotive website (CarsDirect 2010), including Manufacturer’s Suggested Retail Price ($), Dealer Invoice Price ($), fuel tank capacity (gallons), city and highway fuel economy (miles per gallon) and interior volume (cubic feet). Greenhouse gas emissions (tons of CO₂/year) for each vehicle were obtained from the Department of Energy’s Fuel Economy website (DOE 2010), based on 15,000 miles of driving per year split between 55% city driving and 45% highway driving.

A.10. Waiting List Length

The length of the waiting list for new Prius purchase was estimated by analyzing newspaper articles for the period 2000-2010. Articles that referred to a current waiting list for the purchase of a Prius in the US were identified using Factiva. For each month, an estimated waiting list length was calculated as the average of the waitlist estimates mentioned in articles during that month. In addition, the frequency of newspaper references to waiting lists in the US was collated each month. These two data sets have a correlation of 0.68.
Appendix B: Government Incentives - 2000-2010

The details of government incentives available across the United States were gathered from numerous sources, building on the Union of Concerned Scientists’ list of hybrid vehicle incentives (UCS 2010). Here we summarize the details of these incentives as they apply to the Toyota Prius:

Table 20: Details of Government Incentives

<table>
<thead>
<tr>
<th>Region</th>
<th>Type</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Federal Government Incentives</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>National</td>
<td>Tax Deduction</td>
<td>The Clean Fuel Tax Deduction for Hybrids allowed hybrid buyers to claim a $2,000 one-time tax deduction in 2004 or 2005, limited to new vehicles purchased as far back as 2000 (Department of Energy 2006).</td>
</tr>
<tr>
<td>National</td>
<td>Tax Credit</td>
<td>Hybrid vehicles purchased after December 31, 2005 are eligible for a federal income tax credit of up to $3,400. Credit amounts phase out for a given manufacturer after it has sold 60,000 eligible vehicles (Department of Energy 2012).</td>
</tr>
<tr>
<td><strong>State Government Incentives</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arizona</td>
<td>HOV Lane Access</td>
<td>Beginning February 9th 2007, qualifying low emissions vehicles including the Toyota Prius can drive in any HOV lane in Arizona, regardless of the number of occupants. Scheme capped at 10,000 permits (Katz and Shapiro 1994).</td>
</tr>
<tr>
<td>California</td>
<td>HOV Lane Access</td>
<td>From January 2005, hybrid-electric vehicles that get 45mpg and have SULEV emissions ratings displaying the required decal can access HOV lanes (CARB 2011). Capped at 85,000 vehicles. Rescinded on July 1, 2011.</td>
</tr>
<tr>
<td>Colorado</td>
<td>Tax Credit</td>
<td>From July 1st 2000, Colorado residents are about to claim a tax credit of up to $6,000 for the purchase of a hybrid vehicle. The percentage of the incremental cost covered by the tax credit is determined by the emissions standard met by the vehicle (UCS 2010).</td>
</tr>
<tr>
<td>Colorado</td>
<td>HOV Lane Access</td>
<td>From May 15, 2008, qualifying hybrid vehicles displaying the required decal and transponder can access HOV and HOT lanes. Capped at 2,000 vehicles (Colorado DOT 2011).</td>
</tr>
<tr>
<td>Connecticut</td>
<td>Tax Exemption</td>
<td>Between October 1, 2004 and June 30, 2010, hybrids getting at least 40 mpg are exempt from the state's 6% sales tax (Connecticut DRS 2009).</td>
</tr>
<tr>
<td>Washington, D.C.</td>
<td>Tax Exemption and Reduced Registration Fee</td>
<td>From April 2005, owners of hybrids do not pay excise tax (6-7%) and have a reduced registration fee (DC DMV 2005).</td>
</tr>
<tr>
<td>-----------------</td>
<td>---------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Florida</td>
<td>HOV Lane Access</td>
<td>A hybrid vehicle certified by the EPA may be driven in a HOV lane at any time if displaying the appropriate decal (FL HSMV 2008).</td>
</tr>
<tr>
<td>Idaho</td>
<td>Exemption from Emissions Testing</td>
<td>From April 1 2008, hybrid vehicles are exempt from the vehicle emission inspection and maintenance program (Idaho VIP 2010).</td>
</tr>
<tr>
<td>Illinois</td>
<td>Rebate</td>
<td>Illinois residents who purchased a hybrid vehicle using a loan from a participating bank or credit unit were eligible for a $1,000 rebate (UCS 2010).</td>
</tr>
<tr>
<td>Louisiana</td>
<td>Tax Credit</td>
<td>From November 2002, a state income tax credit worth 20 percent of the incremental cost of purchasing an OEM AFV was offered, up to a limit of $1,500 (LA DNR 2012).</td>
</tr>
<tr>
<td>Louisiana</td>
<td>Tax Credit</td>
<td>From July 2009, a state income tax credit worth the lesser of 10 percent of the vehicle cost or $3,000 was offered for the purchase of a hybrid vehicle (LA DNR 2012).</td>
</tr>
<tr>
<td>Maine</td>
<td>Tax Credit</td>
<td>Until 2006, Maine provided a sales tax credit of $500 for hybrid cars for which there is no comparable vehicle powered by gasoline, including the Toyota Prius (UCS 2010).</td>
</tr>
<tr>
<td>Maryland</td>
<td>Tax Credit</td>
<td>From July 1 2000 to July 1 2004, the Maryland Clean Energy Incentive Act provided tax credits against the 5 percent vehicle excise tax up to $1,000 for qualifying HEVs from model year 2000 (Maryland State Dept 2000).</td>
</tr>
<tr>
<td>Maryland</td>
<td>Exemption from Emissions Testing</td>
<td>Qualifying hybrid electric vehicles that achieve a city fuel economy rating of at least 50 mpg are exempt from motor vehicle emissions testing and inspection requirements (Maryland MVA 2012).</td>
</tr>
<tr>
<td>Nevada</td>
<td>Exemption from Emissions Testing</td>
<td>From February 2007, hybrid vehicles less than 5 years old are exempt from emissions testing in Clark and Washoe Counties (NV DMV 2012).</td>
</tr>
<tr>
<td>New Jersey</td>
<td>HOV Lane Access</td>
<td>From May 2006, qualifying hybrid vehicles are allowed to travel in the HOV lanes on the New Jersey Turnpike between Interchange 11 in Woodbridge and Interchange 14 in Newark at peak hours (New Jersey DOT 2006).</td>
</tr>
<tr>
<td>New Mexico</td>
<td>Exemption from Excise Tax</td>
<td>From July 2004 to June 2009, hybrid vehicles with an EPA fuel economy rating of at least 27.5 miles per gallon w't ere eligible for a one-time exemption from the motor vehicle excise tax, worth between $600 and $1,000 (New Mexico EMNRD 2012).</td>
</tr>
<tr>
<td>State</td>
<td>Feature</td>
<td>Details</td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------------------</td>
<td>-------------------------------------------------------------------------</td>
</tr>
<tr>
<td>New York</td>
<td>HOV Lane Access</td>
<td>From March 2006, hybrid vehicles with a highway mpg of at least 45 mpg are exempt from occupancy requirements on the Long Island Expressway (New York DOT 2012).</td>
</tr>
<tr>
<td>New York</td>
<td>Tax Credit</td>
<td>Until December 31, 2006, the Alternative Fuel (Clean Fuel) Vehicle Tax Incentive Program provided a tax credit of up to $3,000 for qualifying hybrid vehicles including the Toyota Prius (NSERDA 2012).</td>
</tr>
<tr>
<td>Oregon</td>
<td>Tax Credit</td>
<td>Until the end of 2009, a tax credit of up to $1,500 is available for the purchase of a HEV. Eligible vehicles include the Toyota Prius (UCS 2010).</td>
</tr>
<tr>
<td>South Carolina</td>
<td>Tax Credit</td>
<td>From June 1st 2006, hybrid vehicles are eligible for a state tax credit equal to 20 percent of the federal tax credit scheduled to begin in tax year 2006 (ignoring the phase-out provisions in the federal scheme) (UCS 2010).</td>
</tr>
<tr>
<td>South Carolina</td>
<td>Tax Exemption</td>
<td>From July 1st 2008, a $300 sales tax rebate is provided against the purchase of a hybrid vehicle (UCS 2010).</td>
</tr>
<tr>
<td>Tennessee</td>
<td>HOV Lane Access</td>
<td>From January 1st 2009, hybrid vehicles are authorized for single-occupant use of HOV lanes with an appropriate decal (Tennessee DOT 2012).</td>
</tr>
<tr>
<td>Utah</td>
<td>HOV Lane Access</td>
<td>Until 31st December 2010, vehicles with C plates for clean fuel vehicles are allowed to travel in HOV lanes regardless of the number of occupants (Utah DOT 2011).</td>
</tr>
<tr>
<td>Virginia</td>
<td>HOV Lane Access</td>
<td>From July 2006, hybrid vehicles registers with clean fuel license plates are permitted to use all HOV lanes in Virginia except the HOV-3 requirement on I-95/395 from 6-9am or 3.30-6pm (Virginia DOT 2012).</td>
</tr>
<tr>
<td>Washington</td>
<td>Exemption from Emissions Testing</td>
<td>From June 2002, hybrid vehicles that obtain have an EPA rating of at least 50 mpg city are exempt from emissions control inspections (WA DOL 2012).</td>
</tr>
<tr>
<td>Washington</td>
<td>Tax Exemption</td>
<td>From January 1 2009-January 1 2011, the state sales tax and use tax do not apply to new passenger vehicles that have a hybrid powertrain and have an EPA-estimated highway miles of at least 40 miles per gallon (WA DOR 2011).</td>
</tr>
<tr>
<td>West Virginia</td>
<td>Tax Credit</td>
<td>Until June 2006, an Alternative Motor Vehicle Tax Credit could be claimed for the incremental cost of purchasing a hybrid vehicle, up to a maximum credit of $3,750 for a passenger vehicle (UCS 2010).</td>
</tr>
</tbody>
</table>
Appendix C: Model Code

Fleet Turnover

Units: vehicles

The installed base of vehicles by technology in region r is the sum of New Vehicles and Used Vehicles.

Units: vehicles

The stock of New Vehicles in region r accumulates new Vehicle Sales (indexed by technology i), and declines as vehicles age, becoming Used Vehicles, or are retired due to crashes and breakdowns.

Used Vehicles ir[Technology, MSA]= INTEG (Vehicle Aging ir[Technology, MSA]-Used Vehicle Retirements ir[Technology, MSA],"Initial Installed Base - Used Vehicles ir"[Technology, MSA])
Units: vehicles

The stock of Used Vehicles in region r accumulates the aging of vehicles that were formerly New Vehicles, and declines as used vehicles are retired due to aging.

Vehicle Sales ir[PRIUS, MSA]=UPL US Quarterly Prius Sales r[MSA]
Units: vehicles/Quarter

For the Prius, the rate of Vehicle Sales entering the fleet in region r is given by the rate of Prius sales occurring at dealerships, as simulated by the model. For the conventional gasoline technology, the rate of Vehicle sales in region r is given by the historic rate of light vehicle sales in the United State, less the rate of Prius sales simulated by the model.

Vehicle Aging ir[Technology, NetworkMSA]=New Vehicles ir[Technology, NetworkMSA]/Aging Time Lambda
Units: vehicles/Quarter

The rate of Vehicle Aging in region r, indexed by technology, is formulated as the stock of New Vehicles by technology, divided by the assumed time for New Vehicles to age and become Used Vehicles.

New Vehicle Retirements ir[Technology, MSA]=NV Discard Fr*New Vehicles ir[Technology, MSA]
Units: vehicles/Quarter

The rate of New Vehicle Retirements due to breakdowns and crashes in region r, indexed by platform, is equal to the stock of New Vehicles multiplied by NV Discard Fr, the fraction of New Vehicles discarded each quarter.

Used Vehicle Retirements ir[Technology, MSA]=Used Vehicles ir[Technology, MSA]/Retirement Time
Units: vehicles/Quarter

The rate of Used Vehicle Retirements in region r, indexed by technology, is equal to the stock of Used Vehicles for each technology, divided by Retirement Time, the average lifetime that a vehicle survives as a Used Vehicle.

"Initial Installed Base - New Vehicles ir"[GAS, MSA]=(1/3)*"UPL MSA Installed Base Cars + Trucks r"[MSA]
"Initial Installed Base - New Vehicles ir"[PRIUS, NetworkMSA]=0
"Initial Installed Base - Used Vehicles ir"[GAS, MSA]=(2/3)*"UPL MSA Installed Base Cars + Trucks r"[MSA]
"Initial Installed Base - Used Vehicles ir"[PRIUS, NetworkMSA]=0
Units: vehicles

Initially, the installed base of Prius vehicles, both New and Used, is zero. Assuming a total installed base of light vehicles in the United States of 234 million vehicles, I assume that one third of the vehicles in each region are New Vehicles, while the remaining two-thirds of vehicles are Used Vehicles.

NV Discard Fr=0.01/4

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The rate of New Vehicle Discards due to breakdowns and crashes is assumed to be 1% per year, equal to 0.01/4 per quarter.

Aging Time Lambda=20
Units: Quarter

The age at which New Vehicles age to become Used Vehicles, defined as Aging Time Lambda, is assumed to be 20 quarters (5 years).

Retirement Time=40
Units: Quarter

The age of which Used Vehicles are retired on average assumed to be 40 quarters (10 years). Thus, the average lifetime of a vehicle in the model is 20 + 40 = 60 quarters (15 years).

New Vehicle Buyers ir[PRIUS,MSA]=UPL US Quarterly Light Vehicle Sales r[MSA]*((Fr New Sales from New Vehicle Drivers*Prius Driver Fr from New Vehicle Retirements and Vehicle Aging r[MSA])+((1-Fr New Sales from New Vehicle Drivers)*Prius Driver Fr from Used r[MSA]))

Units: vehicles/Quarter

The technology currently being driven by the buyer of a new vehicle influences their purchase decision. The number of New Vehicle Buyers who currently own a Prius in region r depends on the fraction of vehicle buyers who currently own a New Vehicle (versus a Used Vehicle), and the fraction of Prius drivers in each of these populations. The balance of New Vehicle Buyers in region r are assumed to drive a conventional gasoline vehicle, calculated as the historic number of light vehicle sales per month less the number of New Vehicle Buyers who drive a Prius.

Prius Driver Fr from New Vehicle Retirements and Vehicle Aging r[MSA]=New Vehicles ir[PRIUS,MSA]/SUM(New Vehicles ir[Technology!,MSA])
Units: dmnl

The fraction of New Vehicle drivers who drive a Prius in region r is given by the number of New Prius vehicles, divided by the total number of New Vehicles.

Prius Driver Fr from Used r[MSA]=Used Vehicles ir[PRIUS,MSA]/SUM(Used Vehicles ir[Technology!,MSA])
Units: dmnl

The fraction of Used Vehicle drivers who drive a Prius in region r is given by the number of used Prius vehicles, divided by the total number of Used Vehicles.

Fr New Sales from New Vehicle Drivers=0.4
Units: dmnl

The fraction of consumers buying a vehicle that currently drive a New Vehicle (i.e. less than 5 years old) is assumed to be 40%.

Customer Wait List and the Vehicle Supply Chain

Wait List= INTEG (Customer Orders-Reneging-Order Fulfilment,0)
Units: vehicles

The wait list for the Prius accumulates new customer orders for the Prius, and declines when Order Fulfillment occurs, or when consumers renege from the wait list.

Customer Demand for Prius r[MSA]=MAX(0,SUM(New Vehicle Buyers ir[Technology!,MSA]*Prius Share of Customer Demand ir[Technology!,MSA])*UPL Car Share of Light Vehicle Sales)
Units: vehicles/Quarter
The level of customer demand for the Prius each quarter in each region is estimated as the market share of Prius within the segment of the light vehicle market that the Prius competes in. The number of New Vehicle Buyers within the Prius segment in region \( r \), indexed by technology, is calculated as New Vehicle Buyers \( i \) multiplied by the fraction of the light vehicles sales that are cars, multiplied by the fraction of the car market occupied by the Prius' segment. Multiplying this by the Prius Share of Customer Demand in region \( r \), indexed by technology, gives the demand for the Prius indexed by technology currently being driven by each buyer. Summing across these technologies gives the total Customer Demand for the Prius.

Customer Orders = \( \text{SUM} \{ \text{Customer Demand for Prius} \, r \{MSA!} \} \)
Units: vehicles/Quarter

The rate of Customer Orders across all dealerships is equal to the sum of Customer Demand for the Prius across all regions \( r \).

Order Fulfillment = Dealer Prius Sales
Units: vehicles/Quarter

The rate of Order Fulfillment from the Prius wait list is equal to the rate at which Dealer Prius Sales are completed, removing vehicles from the Dealer Inventory.

Reneging = \( \text{SW Reneging} \times \text{MAX}(0, \text{Wait List} \times \text{Reneging Fraction}) \)
Units: vehicles/Quarter

The rate of Reneging is equal to the number of customers of the Wait List, multiplied by the Reneging Fraction, the fraction of the Wait List who drop off each quarter. The rate of Reneging must be non-negative, because the Wait List can only be greater than or equal to zero. The switch \( \text{SW Reneging} \) allows the first-order Reneging feedback to be turned on/off.

Reneging Fraction = 0.15
Units: dmnl/Quarter

The rate of reneging from the wait list (customers who join the wait list but subsequently relinquish their place before their order is fulfilled) is assumed to be 15% of the number of customers on the wait list per quarter.

SW Reneging = 1
Units: dmnl

If \( \text{SW Reneging} = 1 \), reneging is enabled in the model. If \( \text{SW Reneging} = 0 \), reneging is disabled in the model (equivalent to the Reneging Fraction = 0).

Dealer Inventory = \( \text{INTEG} \{ \text{Shipments to Dealers} - \text{Dealer Prius Sales}, \text{Initial Dealer Inventory} \} \)
Initial Dealer Inventory = 0
Units: vehicles

The stock of Prius vehicles in the Dealer Inventory accumulates Shipments to Dealers of Prius vehicles, and is reduced as Dealer Prius Sales transactions are completed. Initially, the Dealer Inventory of Prius vehicles is zero, as the model begins before the Prius is introduced into the US market.

Shipments to Dealers = Shipments to US
Units: vehicles/Quarter

The rate at which Prius vehicles are shipped to Toyota dealers, Shipments to Dealers, is equal to the rate at which Prius Shipments arrive in the US from Japan, where Prius vehicles are manufactured.

Shipments to US = \( \text{DELAY}3 \{ \text{UPL Prius Exports to US}, \text{Shipping Delay} \} \)
Units: vehicles/Quarter

Shipments of Prius vehicles to the United States are assumed to follow a third-order delay of exports of Prius vehicles from Japan, accounting for the time to ship vehicles from Japan to the United States and also distribute vehicles to Toyota dealerships within the United States.

Shipping Delay = 0.25
Units: Quarter
The Shipping Delay time from Japan to dealerships in the United States is assumed by be 0.25 quarters.

Dealer Prius Sales=MAX(0, MIN(Maximum Shipping Rate, Desired Shipping Rate)))
Units: vehicles/Quarter

The rate at which Dealer Prius Sales occur is the lesser of the rate at which Prius vehicles can be shipping from the Dealer Inventory (the Maximum Shipping Rate) and the rate at which customers can be retrieved from the wait list (the Desired Shipping Rate). The rate of Dealer Prius Sales must be non-negative, because both the Dealer Inventory and the Wait List can only be greater than or equal to zero.

Maximum Shipping Rate=Dealer Inventory/Minimum Dealer Delay
Units: vehicles/Quarter

The Maximum Shipping Rate given the available Dealer Inventory is calculated as the Dealer Inventory divided by the Minimum Dealer Delay, the minimum time needed to prepare a vehicle from the inventory for sale to a customer.

Minimum Dealer Delay=0.017
Units: Quarter

The Minimum Dealer Delay is assumed to be 0.017 quarters (~1.5 days).

Desired Shipping Rate=(Wait List/Target Delivery Delay)
Units: vehicles/Quarter

The Desired Shipping Rate given the current Wait List is calculated as the Wait List divided by the Target Delivery Delay, the average time needed to contact a customer from the Wait List and for that customer to visit their dealership to complete their purchase transaction.

Target Delivery Delay=0.067
Units: Quarter

The Target Delivery Delay is assumed to be 0.067 months (~6 days).

Inventory Coverage=ZIDZ(Dealer Inventory, Sales Forecast)
Units: Quarter

Dealers use their estimate of their Inventory Coverage (the number of months of inventory they have on hand) to determine whether they should offer incentives to consumers to manage their inventory. Inventory Coverage is calculated as the current level of Dealer Inventory divided by the Sales Forecast.

Sales Forecast=IF THEN ELSE(Time<Prius Introduction Date, 0, (Weight Dealer v Marketing*Dealer Sales Forecast)+((1-Weight Dealer v Marketing)*Initial Marketing Demand Forecast))
Units: vehicles/Quarter

The Sales Forecast used by dealers to estimate their Inventory Coverage is the weighted average of the Dealer Sales Forecast (the forecast they make themselves based on their own experience) and the Initial Marketing Demand Forecast (the forecast provided to the dealerships by the manufacturer), where Weight Dealer v Marketing is the relative weight attached to each forecast. Prior to the introduction of the Prius, the Sales Forecast is zero.

Initial Marketing Demand Forecast=3000
Units: vehicles/Quarter

The Initial Marketing Demand Forecast is assumed to be 3000 vehicles/quarter, based on anecdotal newspaper reports.

Weight Dealer v Marketing=IF THEN ELSE((Cumulative Sales/Ref Cum Sales for Dealer Forecast)<1, Cumulative Sales/Ref Cum Sales for Dealer Forecast, 1)
Units: dmnl

The Weight Dealer v Marketing is the weight attached to the dealer forecast relative to the manufacturer's marketing forecast. The Weight Dealer v Marketing grows linearly with Cumulative Sales until the Reference Cumulative Sales for Dealer Forecast is reached, at which point Weight Dealer v Marketing = 1. Initially, dealers have little or no experience with
the Prius, so they must rely on the manufacturer's marketing forecast until their experience accumulates with cumulative
Prius sales.

Cumulative Sales = \( \text{INTEG} \) (Sales, 0)
Units: vehicles

*Cumulative Sales of the Prius is the accumulation of monthly Sales of the Prius over time.*

Ref Cum Sales for Dealer Forecast = 10000
Units: vehicles

*The Reference Cumulative Sales for the Dealer Forecast is assumed to be 10000 vehicles.*

Dealer Sales Forecast = (Weight Orders \( v \) Sales * Expected Sales from Customer Orders) + ((1 - Weight Orders \( v \) Sales) * Expected Sales from Dealer Sales)
Units: vehicles/Quarter

*When dealerships forecast their rate of Prius sales, they could look to the rate of which Prius sales are being completed, or the rate of which Customer Orders are arriving at their dealership, or both. Here, the Dealer Sales Forecast is the weighted average of Expected Sales from Customer Orders and Expected Sales from Dealer Sales.*

Expected Sales from Dealer Sales = SMOOTH N (Dealer Prius Sales, Sales Smoothing Time, Initial Marketing Demand Forecast, 3)
Units: vehicles/Quarter

*Expected Sales from Dealer Sales is assumed to be a third-order smoothing of the monthly rate of Dealer Prius Sales, smoothed over the Sales Smoothing Time. Initially, the Marketing Demand Forecast is used in the absence of historic Dealer Prius Sales to base the forecast on.*

Expected Sales from Customer Orders = SMOOTH N (Customer Orders, Sales Smoothing Time, Initial Marketing Demand Forecast, 3)
Units: vehicles/Quarter

*Expected Sales from Customer Orders is assumed to be a third-order smoothing of the monthly rate of Customer Orders, smoothed over the Sales Smoothing Time. Initially, the Marketing Demand Forecast is used in the absence of historic Dealer Prius Sales to base the forecast on.*

Sales Smoothing Time = 1
Units: Quarter

*The Sales Smoothing Time over which dealerships smooth their forecasts is assumed to be one quarter.*

Weight Orders \( v \) Sales = 1
Units: \( \text{dmnl} \)

*I assume that dealerships base their dealer sales forecast exclusively on Expected Sales from Customer Orders, which is arguably a better measure of customer demand than Expected Sales from Dealer Sales, which can be biased by supply constraints.*

**Consumer Familiarity**

Familiarity with Prius \( r \) [MSA] = \( \text{ZIDZ} \) (Total Familiarity with Prius \( r \) [MSA], Installed Base \( r \) [GAS, MSA])
Units: \( \text{dmnl} \)

*Familiarity is modeled using a co-flow structure to keep track of the effect of fleet turnover on consumer familiarity. The average Familiarity with Prius in region \( r \) is calculated as the gasoline vehicle population's Total Familiarity with the Prius, measured in vehicles, divided by the Installed Base of gasoline vehicles. This formulation implicitly assumes that the gasoline driver population is well mixed and have similar social habits.*

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Total Familiarity with Prius \( r[\text{MSA}] = \text{INTEG} (\text{Familiarity Update} \ r[\text{MSA}] + \text{Total Familiarity Gain Prius} \ r[\text{MSA}] - \text{Total Familiarity Loss Prius} \ r[\text{MSA}], \text{Initial Familiarity with Prius}[\text{MSA}] ) \)

Units: vehicles

Gasoline drivers' Total Familiarity with the Prius in region \( r \) accumulates social exposure to the Prius from marketing and word-of-mouth, Familiarity Update, plus Familiarity gained who drivers of the Prius revert to driving a gasoline vehicle, Total Familiarity Gain Prius, and decreases when drivers of gasoline vehicles adopt the Prius, Total Familiarity Loss Prius. Initially, this stock takes the value Initial Familiarity with Prius.

Initial Familiarity with Prius = 0
Units: vehicles

The Initial Familiarity drivers of conventional gasoline vehicles have with the Prius is assumed to be zero.

Familiarity Update \( r[\text{MSA}] = (\text{Familiarity Gain} \ r[\text{MSA}] - \text{Familiarity Loss} \ r[\text{MSA}]) \times \text{Installed Base ir[GAS,MSA]} \)

Units: vehicles/Quarter

Gasoline driver socialization and forgetting happens at the individual level. However, the co-flow structure in the model maintains Familiarity at the population level. The rate of Familiarity Update in the gasoline driver population in region \( r \) due to socialization and forgetting is calculated as the net effect of Familiarity Gain (socialization) less Familiarity Loss (forgetting), multiplied by the Installed Base of gasoline vehicles.

Familiarity Gain \( r[\text{MSA}] = \text{Total Social Exposure to Platform} \ r[\text{MSA}] \times (1 - \text{Familiarity with Prius} \ r[\text{MSA}]) \)

Units: dmnl/Quarter

Gasoline drivers gain familiarity to the Prius through social exposure, assumed to occur at a diminishing rate as socialization saturation occurs. The Familiarity Gain made by gasoline vehicle drivers as a result of social exposure to the Prius (through marketing and word-of-mouth) in region \( r \) is calculated as the Total Social Exposure to the Prius Platform multiplied by 1-Familiarity with Prius, the remaining Familiarity potential that exists in the gasoline driver population.

Total Social Exposure to Platform \( r[\text{MSA}] = \text{Social Exposure to Platform within Region} \ r[\text{MSA}] + \text{Socialization Effect of Out-of-Region Prius Drivers} \ r[\text{MSA}] \)

Units: dmnl/Quarter

Total Social Exposure to the Prius in region \( r \) is the sum of Social Exposure to the Prius within Region \( r \), plus the Socialization Effect of Out-of-Region Prius Drivers across social network ties.

Social Exposure to Platform within Region \( r[\text{MSA}] = \text{Socialization Effect of National Marketing} + \text{Socialization Effect of Regional Marketing} \ r[\text{MSA}] + \text{Socialization Effect of Prius Drivers} \ r[\text{MSA}] \)

Units: dmnl/Quarter

The social exposure to the Prius that consumers in region \( r \) receive is the sum of the Socialization Effect of National Marketing, the Socialization Effect of State Marketing and the Socialization Effect of Prius Drivers through word-of-mouth. All regions are exposed to national marketing equally.

Socialization Effect of National Marketing = Effectiveness of National Marketing \( \times (\text{National Marketing Spend}/\text{Dollars per Million}) \)

Units: dmnl/Quarter

Following the standard Bass model, the Socialization Effect of National Marketing is equal to the amount spent marketing the Prius by Toyota each quarter in national media outlets, National Marketing Spend, converted to millions by dividing by Dollars per Million, multiplied by the Prius Marketing Effectiveness coefficient.

Socialization Effect of Regional Marketing \( r[\text{MSA}] = \text{Effectiveness of Regional Marketing} \times (\text{Regional Marketing Spend} \ r[\text{MSA}]/\text{Dollars per Million}) \)

Units: dmnl/Quarter

In addition to national marketing that reaches all regions, marketing occurs in individual regions also. The Socialization Effect of Regional Marketing in region \( r \) is equal to the amount spent marketing the Prius in region \( r \), converted to millions, multiplied by the Effectiveness of Regional Marketing.
Effectiveness of National Marketing = 0
Effectiveness of Regional Marketing = 0
Units: dmnl/million

The Effectiveness of National Marketing and the Effectiveness of State Marketing are parameters estimated empirically, assuming constant returns on marketing effort both temporally and spatially.

Dollars per Million = 1e+06
Units: $/million

Dollars per Million is equal to 1 million, used to convert from dollars to millions of dollars.

Socialization Effect of Prius Drivers r[MSA] = Probability of Contact with Prius Driver r[MSA] \times \text{Effective Contact Rate Prius Drivers}
Units: dmnl/Quarter

Inspired by the word-of-mouth formulation in the Bass model, the Socialization Effect of Prius Drivers in region r is the product of the rate at which effective contacts occur in the community in region r, the Effective Contact Rate Prius Drivers, and the likelihood that those contacts are with Prius drivers, the Probability of Contact with Prius Drivers. As in the Bass model, this formulation assumes that gasoline vehicle drivers and Prius vehicle drivers are well mixed in the community.

Probability of Contact with Prius Driver r[MSA] = \left( \frac{\text{Installed Base ir[PRIUS,MSA]}}{\text{SUM(Installed Base ir[Technology!,MSA])}} \right)
Units: dmnl

The Probability of Contact with a Prius Driver in region r is equal to the Installed Base of Prius vehicles in region r, divided by the total Installed Base of vehicles of all technologies in region r.

Effective Contact Rate Prius Drivers = 0
Units: dmnl/Quarter

The Effective Contact Rate with Prius Drivers is the net rate at which contacts between potential adopters and adopters results in adoption of the Prius. This parameter represents the net effect of the contact rate and adoption rate parameters in the standard Bass model. This parameter is estimated empirically.

"Socialization Effect of Out-of-Region Prius Drivers r"[MSA] = Effective Contact Rate OutOfRegion Prius Drivers \times \text{SUM(Socialization Matrix Prius rs[MSA,NetworkMSA])/UPL Population r[MSA]}
Units: dmnl/Quarter

The socialization effect of Prius drivers in other regions on consumers in region r depends on the number of Prius drivers in each other region, the strength of social network ties between those regions. Here, assuming the radiation network topology described in the paper, the Socialization Effect of Out-of-Region Prius Drivers on region r is equal to the sum of all network-weighted effective Prius contacts across all regions other than r, represented by the Socialization Matrix Prius, multiplied by the Effective Contact Rate OutOfRegion Prius Drivers, divided by the population of region r, to control for the size of the population over which this information is shared.

Socialization Matrix Prius rs[MSA,NetworkMSA] = UPL Social Network Matrix rs[MSA,NetworkMSA] \times \text{Probability of Contact with Prius Driver r[NetworkMSA]}
Units: dmnl/Quarter

The Socialization Matrix Prius calculates for each region r the probability of coming into contact with a Prius driver in each other region, equal to the social network tie that exists between region r and each other region, Social Network Matrix, multiplied by the Probability of Contact with a Prius Driver in that other region.

Effective Contact Rate OutOfRegion Prius Drivers = 0
Units: dmnl

The Effective Contact Rate with OutOfRegion Prius Drivers is the net rate at which contacts between potential adopters and adopters across between-region social network ties result in adoption of the Prius. This parameter represents the net effect of the contact rate and adoption rate parameters in the standard Bass model, disaggregated spatially. This parameter is estimated empirically.
Drivers of gasoline vehicles may forget about the Prius if they do not receive regular social exposure to the new technology. The rate of Familiarity Loss in region r is calculated as the current level of Familiarity with the Prius in region r, multiplied by the assumed Normal Forget Rate Phi, multiplied by the Effect of Social Exposure on Forgetting in region r.

Effect of Social Exposure on Forgetting $r$, Familiarity $F_p$, Normal Forget Rate $\Phi$, Social Exposure Offset $\eta_{ref}$, Total Social Exposure $s_r$

$$\text{Effect of Social Exposure on Forgetting}(r) = 1 - (0 + (1 - 0) \times \exp(4 \times \varepsilon \times (Total Social Exposure to Platform(r) - Social Exposure Offset \eta_{ref})))/(1 + \exp(4 \times \varepsilon \times (Total Social Exposure to Platform(r) - Social Exposure Offset \eta_{ref})))$$

Here I suggest the Effect of Social Exposure on Forgetting is non-linear: consumers are likely to forget about the Prius more quickly when their level of Familiarity with the Prius is low; conversely, their rate of forgetting is likely to be low when their level of Familiarity is high. Here the Effect of Social Exposure on Forgetting in region r is formulated as a decreasing logistic function with parameters $\varepsilon$ and Social Exposure Offset $\eta_{ref}$. When Familiarity approaches 0, the Effect of Social Exposure on Forgetting approaches 1. When Familiarity approaches 1, the Effect of Social Exposure on Forgetting approaches 0.

$\varepsilon = 7$
Units: Quarter

The forgetting parameter $\varepsilon$ is assumed to be 7.

Social Exposure Offset $\eta_{ref} = 0.15$
Units: $\text{dmnl}/\text{Quarter}$

The forgetting parameter Social Exposure Offset $\eta_{ref}$ is assumed to be 0.15.

Normal Forget Rate $\Phi = 0.075$
Units: $\text{dmnl}/\text{Quarter}$

The rate of which gasoline drivers lose Familiarity with the Prius due to forgetting, the Normal Forget Rate $\Phi$, is assumed to be 0.075 (7.5% per quarter).

Total Familiarity Gain Prius $r$, Familiarity of Prius Discarders $F_p$, Discards Prius to Gas $r$, Endogenous Drivers $o$

$$\text{Total Familiarity Gain Prius}(r) = \text{Familiarity of Prius Discarders} \times \text{Discards Prius to Gas}(r) \times \text{SW Endogenous Drivers}$$

Units: vehicles/Quarter

When a driver who currently drives a Prius reverts back and buys a gasoline vehicle, the installed base of gasoline vehicles in region r is increased by one (assuming the Prius vehicle is retired), and the population of gasoline vehicle drivers gains the Familiarity with the Prius that driver had. Here the Total Familiarity Gain each month in region r as a result of this fleet turnover is calculated as the number of Discard Prius to Gas per month in region r, multiplied by the Familiarity with the Prius of those drivers.

Discards Prius to Gas $r$, Prius Market $r$

$$\text{Discards Prius to Gas}(r) = \sum \text{Share of Prius Discarders} \times \text{Discards Prius to Gas}(r) \times \text{Size of Prius Market}(r)$$

Units: vehicles/Quarter

The number of Discard Prius to Gas in region r in vehicles/month, is equal to the Size of the Prius Market in region r, multiplied by the fraction of those drivers who currently drive a Prius, Prius Discard Fr, multiplied by the share of those Prius drivers who chose to revert to a gasoline vehicle, calculated by multiplying Select Prius to Gas with Share ij and summing across all technologies.

$$\text{Select Prius to Gas}(\text{Technology}, \text{TechnologyTo}) = \text{IF THEN ELSE}(\text{TechnologyTo} = \text{GAS} \text{AND} \text{Technology} = \text{PRIUS}, 1, 0)$$

Units: $\text{dmnl}$

Select Prius to Gas is a binary variable that identifies drivers currently driving a Prius who revert back to the conventional gasoline vehicle. It takes the value 1 if Technology = PRIUS and TechnologyTo = GAS, and 0 otherwise.
The Prius Discard Fraction, the fraction of discards who currently drive a Prius, is the number of New Vehicle Buyers who currently drive a Prius in region r, divided by the total number of New Vehicle Buyers across all technologies in region r.

Familiarity of Prius Discarders = 1
Units: dmnl

The Familiarity of Prius Discarders is assumed to be one, because these drivers have experienced the Prius firsthand, providing the opportunity to learn the unique attributes of this technology.

Total Familiarity Loss Prius r[MSA] = \text{MAX}(0, \text{Familiarity with Prius r[MSA]} \times \text{Sales Prius from Gas r[MSA]} \times \text{SW Endogenous Drivers})
Units: vehicles/Quarter

When a driver who currently drives a gasoline vehicle buys a Prius in region r, the installed base of gasoline vehicles is decreased by one (assuming the gasoline vehicle is retired), and the population of gasoline vehicle drivers in region r lose the Familiarity with the Prius that driver had. Here the Total Familiarity Loss each month as a result of this fleet turnover is calculated as the number of Sales Prius from Gas per month, multiplied by the Familiarity with the Prius of those drivers in region r.

Sales Prius from Gas r[NetworkMSA] = \text{SUM}(\text{Share ijr}[Technology!,TechnologyTo!]*\text{Select Gas to Prius}[Technology!,TechnologyTo!]*\text{Gas Discard Fr}[NetworkMSA]*\text{Size of Prius Market}[NetworkMSA])
Units: vehicles/Quarter

The number of Sales Prius from Gas, in region r in vehicles/month, is equal to the Size of the Prius Market in region r, multiplied by the fraction of those drivers who currently drive a gasoline vehicle, Gas Discard Fr, multiplied by the share of those drivers who chose to purchase a Prius in region r, calculated by multiplying Select Gas to Prius with Share ijr and summing across all technologies.

Size of Prius Market[NetworkMSA] = UPL US Quarterly Light Vehicle Sales r[NetworkMSA] \times UPL Car Share of Light Vehicle Sales \times UPL Prius Class Share of Car Segment
Units: vehicles/Quarter

The Size of the Prius Market each month in region r is equal to the total number of light vehicle sales in region r each quarter, UPL US Quarterly Light Vehicle Sales, multiplied by the car share of the light vehicle market each month, UPL Car Share of Light Vehicle Sales, multiplied by the size of the segment the Prius is competing in, UPL Prius Class Share of Car Segment. The first generation Prius was a Compact Car, while the second and third generation Prius vehicles are Mid-size Cars.

Gas Discard Fr[NetworkMSA] = \text{ZIDZ}(\text{New Vehicle Buyers ir}[GAS,NetworkMSA],\text{SUM}(\text{New Vehicle Buyers ir}[Technology!,NetworkMSA]))
Units: dmnl

The Gas Discard Fraction is the number of New Vehicle Buyers who currently drive a gasoline vehicle in region r, divided by the total number of New Vehicle Buyers across all technologies in region r.

Select Gas to Prius[Technology,TechnologyTo] = IF \text{THEN ELSE}(\text{Technology} = \text{GAS AND TechnologyTo} = \text{PRIUS}, 1, 0)
Units: dmnl

Select Gas to Prius is a binary variable that identifies drivers currently driving a gasoline vehicle who switch to the Prius. It takes the value 1 if Technology = GAS and TechnologyTo = PRIUS, and 0 otherwise.

Vehicle Utility and Vehicle Market Share

Prius Share of Customer Demand ir[Technology,MSA] = \text{IF THEN ELSE}((\text{Time} < \text{Prius Introduction Date}, 0, \text{SUM}(\text{Share ijr}[Technology,TechnologyTo!,MSA] \times \text{Matrix Entrant Selection ij}[Technology,TechnologyTo!])))
Units: dmnl
The Prius Share of Customer Demand is the percentage market share of the Prius in region \( r \), indexed by the technology \( i \) currently being used by drivers. Prius to the Prius Introduction Date, the Prius market share is zero. The market Share is multiplied by the Matrix Entrant Selection variable, zeroing the Share of technologies where the technology is not the Prius. Summing across technology \( j \) (TechnologyTo) results in the Prius Share of Customer Demand by the technology \( i \) currently being driven by the customers.

\[
\text{Share} \, ijr[\text{Technology,TechnologyTo,MSA}]=\text{Affinity} \, ijr[\text{Technology,TechnologyTo,MSA}]/\text{SUM} \{\text{Affinity} \, ijr[\text{Technology,TechnologyTo,MSA}]\}
\]

Units: dmnl

The market Share of technology \( j \) for owners of technology \( i \) in region \( r \) is estimated as the Affinity they have with technology \( j \), divided by the sum of the Affinity they have with all technologies.

\[
\text{Affinity} \, ijr[\text{Technology,TechnologyTo,MSA}]=\text{Familiarity} \, ijr[\text{Technology,TechnologyTo,MSA}] \times \text{EXP Utility} \, jr[\text{TechnologyTo,MSA}]
\]

Units: dmnl

The Affinity that drivers of technology \( i \) have with technology \( j \) in region \( r \) is equal to the Familiarity drivers of technology \( i \) have with technology \( j \), multiplied by the exponential of the utility of technology \( j \).

\[
\text{EXP Utility} \, jr[\text{TechnologyTo,MSA}]=\text{EXP} \{\text{Utility} \, jr[\text{TechnologyTo,MSA}]\}
\]

Units: dmnl

\[\text{EXP Utility is equal to the exponential of the utility of technology } j \text{ in region } r. \text{ This intermediate step is calculated before the effect of Familiarity is incorporated, to ensure that the choice formulation is globally robust to negative utility values.}\]

\[
\text{Familiarity} \, ijr[\text{Technology,TechnologyTo,MSA}]=\text{IF THEN ELSE} \{\text{Technology=GAS:AND:TechnologyTo=PRIUS,IF THEN SW Endogenous Familiarity=0, Exogenous Familiarity Value, Familiarity with Prius r[MSA]),1}\)
\]

Units: dmnl

The Familiarity that drivers of technology \( i \) in region \( r \) have with technology \( j \) depends on the specific combination of technologies \( i \) and \( j \). I assume that all drivers are fully familiar with the conventional gasoline technology (i.e. Familiarity \( ij[\text{Technology}[\text{GAS}]=1 \). I also assume that drivers who have already adopted the Prius are fully familiar with the Prius (i.e. Familiarity \( ij[\text{PRIUS}][\text{PRIUS}=1 \). Therefore, the familiarity dynamics calculated by the model, Familiarity with Prius, only applies in the case where Technology=GAS and TechnologyTo=PRIUS.

\[
\text{Matrix Entrant Selection} \, ij[\text{Technology,TechnologyTo}]=\text{IF THEN ELSE}(\text{TechnologyTo=PRIUS,1,0)}
\]

Units: dmnl

The variable Matrix Entrant Selection is a matrix of binary variables used to signify when the technology being considered (TechnologyTo) is the Prius.

\[
\text{Utility} \, jr[\text{GAS,MSA}]=U1 \, jr[\text{GAS,MSA}]+U2 \, jr[\text{GAS,MSA}]+U3 \, jr[\text{GAS}]+\text{Constant Gas Vehicle}
\]

\[
\text{Utility} \, jr[\text{PRIUS,MSA}]=U1 \, jr[\text{PRIUS,MSA}]+U2 \, jr[\text{PRIUS,MSA}]+U3 \, jr[\text{PRIUS}]+U7 \, r[MSA]+U8 \, r[MSA]+U9 \, r[MSA]+U10 \, r[MSA]+U11 \, r[MSA]
\]

Units: dmnl

The Utility of technology \( j \) is the sum of the effect of the observable attributes of each technology. Here the Utility functions for both the GAS and PRIUS technologies include the technological attributes Purchase Price (U1), Operating Cost (U2), Greenhouse Gas Emissions (U3). The PRIUS Utility function also includes the demographic attributes Political Preference (U4), Educational Attainment (U5), Dealerships (U6) and Vehicle Miles Traveled (U7). Finally, the GAS Utility function includes a constant (Constant Gas Vehicle), capturing all other unobserved utility attributes.

Prius Introduction Date=2
Units: Quarter

The Prius is introduced into the market in the second quarter of 2000 (April 2000).

SW Endogenous Familiarity=1
If SW Endogenous Familiarity=1, Familiarity is calculated endogenously in the model. If SW Endogenous Familiarity=0, the Exogenous Familiarity Value is used.

Exogenous Familiarity Value=1
Units: dmnl

The Exogenous Familiarity Value is the level of familiarity assumed if SW Endogenous Familiarity=0. Exogenous Familiarity Value=1 represents full information, as in the economically rational model of decision making.

\[ U_1 \text{jr[TechnologyTo, MSA]} = ZIDZ \left( \left\{ \frac{\text{Effective Price jr[TechnologyTo, MSA]}}{1000} \right\} \ln(\text{Household Income}_r[\text{MSA}]) \right) \times \text{Purchase Price Weight} \]
Units: dmnl

The effect of the purchase price of technology j on utility in region r, \( U_1 \), is formulated as a function of both the effective purchase price of the technology and the household income of the consumer. Specifically, \( U_1 \) is estimated as the Effective Price of technology j in region r (in thousands of dollars), divided by the natural log of Household Income in region r (in thousands of dollars), multiplied by the Purchase Price Weight. Taking the natural log of Household Income captures the concept that consumers become less sensitive to price as their income increases.

Effective Price jr[PRIUS, MSA]=UPL MSRP [jPRIUS]-"UPL Federal Tax Credit - Prius"-"UPL State Government Incentives - Prius r[MSA]-UPL HOV Lane Incentive r[MSA]-Dealer Incentive
Effective Price jr[GAS, NetworkMSA]=UPL MSRP [jGAS]
Units: $/vehicles

The Effective Price of the Prius in region r is assumed to be the Manufacturers Suggested Retail Price (MSRP) less applicable Federal and State government incentives in region r and any incentive offered by the Toyota dealership. The Effective Price of the conventional gasoline vehicle is assumed to simply be the Manufacturers Suggested Retail Price.

\[ U_2 \text{jr[TechnologyTo, MSA]} = \text{Operating Cost Weight} \times \text{Operating Cost jr[TechnologyTo, MSA]} \]
Units: dmnl

The effect of operating on utility of technology j, \( U_2 \), is equal to the operating cost of technology j in region r in cents per mile, multiplied by the weight placed on this attribute, Operating Cost Weight.

Operating Cost jr[Technology, MSA]=ZIDZ(UPL US Average Retail Gasoline Price r[MSA],"UPL MPG (Combined) j[Technology])\times 100
Units: cents/miles

The Operating Cost of technology j in region r (cents/mile) is calculated as the US Average Retail Gasoline Price in region r (in cents/gallon) divided by the fuel economy of technology j (miles/gallon).

\[ U_3 \text{j[TechnologyTo]} = \text{Emissions Fr Weight} \times \text{UPL Emissions Fraction j[TechnologyTo]} \]
Units: dmnl

The effect of greenhouse gas emissions on the utility of technology j, \( U_3 \), is equal to the Emissions Fraction Weight multiplied by the greenhouse gas emissions by technology, measured as annual greenhouse gas emissions as a fraction of the annual greenhouse gas emissions of an equivalent gasoline vehicle.

\[ U_4 r[MSA] = \text{UPL Political Preference r[MSA]} \times \text{Political Preference Weight} \]
Units: dmnl

The effect of consumer political preference on the utility of the Prius in region r, \( U_4 \), is equal to the Political Preference Weight multiplied by % of population in region r who voted for the Democratic candidate in the 2008 presidential election.

\[ U_5 r[MSA] = \text{UPL Educational Attainment r[MSA]} \times \text{Educational Attainment Weight} \]
Units: dmnl
The effect of consumer educational attainment on the utility of the Prius in region \( r \), \( U_6 \), is equal to the Educational Attainment Weight multiplied by the percentage of the population in region \( r \) age 25 or over who hold a bachelor's degree or higher.

\[ U_6 \text{[MSA]} = \text{Dealerships Weight} \times \text{UPL Toyota Dealerships r[MSA]} \]
Units: dmnl

The effect of consumer political preference on the utility of the Prius in region \( r \), \( U_6 \), is equal to the Political Preference Weight multiplied by the number of Toyota dealerships in region \( r \).

\[ U_7 \text{[MSA]} = \text{VMT Weight} \times \left( \frac{\text{UPL VMT r[MSA]}}{1000} \right) \]

The effect of consumer vehicle miles travelled in region on the utility of the Prius, \( U_7 \), is equal to the VMT Weight multiplied by the annual vehicle miles travelled, measured in thousands of miles.

Purchase Price Weight=0 [Units: dmnl/($/vehicles)]
Operating Cost Weight=0 [Units: dmnl/(cents/miles)]
Emissions Fr Weight=0 [Units: dmnl]
Political Preference Weight=0 [Units: dmnl]
Educational Attainment Weight=0 [Units: dmnl/% 25+ with bachelors degree or higher]
Dealerships Weight=0 [Units: dmnl/dealerships]
Constant Gas Vehicle=0 [Units: dmnl]

Weights for the contribution of each attribute to consumer utility are estimated empirically, assuming an initial value of zero (i.e. the attribute does not contribute to consumer utility). These weights are assumed to be constant and invariant across geographic regions.

Dealer Incentive=IF THEN ELSE (SW UPL Incentives for Testing=1, UPL Dealer Incentives, IF THEN ELSE(Days to Turn<=0, 0, MAX(0, Max Dealer Incentive-Coefficient*(Days to Turn^PPower))))
Units:$/vehicles

The Dealer Incentive offered for the Prius is formulated using a standard power-law, capturing the non-linear response between inventory coverage (Days to Turn) and the incentive offered. As the Days to Turn each Prius vehicle increases, greater incentives are needed to sell the vehicle in order to manage dealer inventory. First I assume that a Maximum Dealer Incentive exists, representative of the difference between the MSRP and the Dealer Invoice price the dealer paid for the vehicle. The Dealer Incentive is calculated as the Max Dealer Incentive less the profit made by the dealer, calculated as a power-law based on Days to Turn with power PPower.

PPower=-0.69
Units: dmnl

The power law parameter PPower is assumed to be -0.69, based on empirical analysis of Prius transaction data.

Coefficient=7256
Units:$/vehicles

The power law parameter Coefficient is assumed to be 7256, based on empirical analysis of Prius transaction data.

Max Dealer Incentive=3000
Units:$/vehicles

The maximum incentive offered by dealers to encourage sales of the Prius is assumed to be $3,000, representative of the average difference between the Manufacturer's Suggested Retail Price for the Prius and the Dealer Invoice price charged to dealers when they purchase inventory.

SW UPL Incentives for Testing=0
Units: dmnl

If SW UPL Incentives for Testing=0, the Dealer Incentive is calculated endogenously in the model. If SW UPL Incentives for Testing=0, the historic Prius Dealer Incentive data uploaded into the model is used.
Days to Turn = Inventory Coverage * Correction Days per Month
Units: days

The average number of days needed to turn over a vehicle in the dealer's inventory (that is, the difference between the sale date and the date the vehicle was delivered to the dealer) is equal to the current inventory coverage in months, multiplied by the number of Days per Month, to convert to days.

Correction Days per Month = 30
Units: days/Month

This units correction is used to convert inventory coverage, measured in months, to days for the dealer incentive calculation.
Essay 3: Bridge to Where? Do Hybrid Vehicles Help or Hinder the Transition to Plug-In Electric Vehicles?

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Abstract
Gasoline hybrid-electric vehicles (HEVs) have enjoyed considerable success in the United States over the past decade, assisted by government policies to promote HEV adoption such as income tax credits and access to high-occupancy vehicle (HOV) lanes. Recently, many HEV incentives have ended, as policy-makers move to promote consumer adoption of recently introduced electric vehicles such as the Chevrolet Volt plug-in hybrid-electric vehicle and the Nissan Leaf battery-electric vehicle. In this paper I explore consumer adoption of hybrid and electric vehicles (EVs), focusing on the transitional role of HEVs. The dominant theory from the technology strategy literature suggests that the success of HEVs should benefit the transition to more radical plug-in electric vehicles, building producer experience and consumer familiarity with the electric powertrain. However, HEVs have considerable appeal in the short and medium term, with a lower incremental purchase price and compatibility with the existing gasoline infrastructure. I develop a model of innovation diffusion with multiple competing but related entrant technologies. I find that the smooth transition from HEVs to EVs is possible but not assured, identifying public policy and firm strategy decisions that have the potential to accelerate this transition.
1. Introduction

Since the beginning of the 20th century, oil has been a fundamental enabler of economic development. Inexpensive and easy to distribute, oil-based fuels such as petrol and diesel have facilitated the effective movement of people and goods by road, rail and air. However, there is increasing interest in transitioning away from dependence on oil for automotive transportation, motivated by concerns about rising and increasingly volatile oil prices, and greenhouse gas emissions and particulate emissions resulting from the combustion of oil-based fuels.

The steady growth in HEV adoption in the US over the past decade represents an important achievement in reducing US dependence on oil for automotive transportation. HEVs improve the efficiency of gasoline consumption using technologies including electric drive powered by regenerative braking, and automatic stop/start, but do not refuel from the electricity grid directly. Since the Honda Insight HEV was first introduced in 1999, over two million HEVs have been sold in the United States, with the iconic Toyota Prius achieving over one million of sales alone (MyNissanLeaf.com 2010; WardsAuto 2011). Today, more than 30 models of HEV are available in the US, reflecting growing consumer acceptance of this technology. Yet, the installed base of HEVs represents less than 1% of the US light duty vehicle fleet, highlighting the scale of the technology transition challenge.

The arrival of plug-in electric vehicles in late 2010, led by the Chevrolet Volt plug-in hybrid-electric vehicle (PHEV) and the Nissan Leaf battery-electric vehicle (BEV), marks the latest attempt to introduce alternative fuel vehicles (AFVs) in the United States. Both PHEVs and BEVs recharge directly from the electricity grid, unlike conventional HEVs. However, whereas BEVs run exclusively on electricity, PHEVs combine an electric powertrain with a conventional gasoline engine, either in series or parallel, providing both electric driving and extended vehicle range. Plug-in electric vehicles offer superior energy efficiency (Bandivadekar, Bodek et al. 2008), and, if the electricity to power them can be generated from renewable sources, hold the potential for deep reductions in greenhouse gas emissions and gasoline use (Kromer 2007). Automakers including Ford, Toyota, BMW, Volkswagen and Volvo, and startups such as Tesla, Fisker and Coda plan to introduce many EV models in coming years. However, despite the considerable technological potential of EVs, the future success of the technology is far from assured. Early EVs are expensive and have a limited electric range, owing to the high unit cost and relatively low energy density of lithium-ion batteries, and lack the ubiquitous refueling infrastructure available to gasoline vehicles.
With consumers now able to choose from multiple hybrid and electric vehicles, the evolution of the automotive market is not immediately obvious. While the extensive innovation diffusion literature provides numerous insights about the factors governing consumer adoption of a single technology, relatively little has been written about markets that have multiple competing entrants and where those entrants are related to each other. The nascent state of the electric vehicle market gives rise to the two research questions considered in this paper: First, how does the presence of multiple competing entrant platforms influence the dynamics of technology diffusion? Second, do policies that encourage consumer adoption of hybrid-electric vehicles benefit the transition to plug-in electric vehicles? The dominant theory from the technology strategy literature implies that the current build-up of conventional gasoline hybrids will benefit the transition to more radical plug-in electric vehicles over time, accumulating producer experience and consumer familiarity with the electric powertrain. However, the demonstrated attractiveness of conventional gasoline hybrids may itself hinder the transition to plug-in electric vehicles, providing consumers considerable fuel economy improvements at low incremental cost, without the need for the development of a new and ubiquitous recharging infrastructure.

Government policy has played an significant role in the formation of a market for HEVs (Diamond 2009), with numerous incentives offered by federal and state governments such as tax credits and high-occupancy vehicle (HOV) lane access, as discussed in Essays 1 and 2. Not all incentives are equally effective on a dollar-for-dollar basis. For example, sales tax waivers at the time of purchase have been found to be much more effective than tax credits that are realized on the consumer's income tax return (Sims Gallagher and Muehleggger 2008). Given the promise of EVs, it is not surprising that governments have sought to accelerate consumer adoption of EVs also. Plug-in electric vehicles purchased after 31st December 2009 qualify for a federal tax credit of between $2,500 and $7,500, depending on the vehicle's battery capacity (DOE 2012), and an EV infrastructure tax credit was available until December 31st 2011, providing consumers a tax credit for 30% of the cost of installing a recharging station up to a cap of $1,000 (Plug In America 2012). In addition, 26 states provide some form of incentive for electric vehicle adoption, such as California's $2,500 Clean Vehicle Rebate for electric vehicles (CCSE 2012). However, the introduction of these EV incentives has coincided with the expiration of many HEV incentives. Many commentators have suggested that hybrid vehicles are now widely accepted by consumers, implying that incentives are no longer needed to sustain the market. According to the Mike Stanton, CEO of the Association of International Automobile Manufacturers, "The intent was to provide an incentive for new technology...Hybrid technology is now pretty well known"
However, the removal of these incentives may be premature in light of the 'sizzle and fizzle' dynamics observed in previous efforts to introduce AFVs. For example, sales of compressed natural gas vehicles grew rapidly in New Zealand in the early 1980s, before collapsing when incentives were removed in 1985.

In this paper I introduce a formal model of the automotive technology diffusion to explore the dynamics of the emerging market for hybrid and electric vehicles. First, I detail the arguments for and against the theory that HEVs play a transitional role within the EV market. Second, I develop a model of technology diffusion that captures consumer choice between multiple vehicle platforms in the presence of OEM and consumer learning, the spillovers of learning between platforms and the coevolution of refueling infrastructure. Third, I use the model to explore a number of future market scenarios that inform our understanding of how the sustained adoption of HEVs may influence the emerging market for EVs. I find that both competitive forces and the extent of spillovers of familiarity and marketing influence the rate at which this transition occurs. Pricing carbon is identified as a key policy that accelerates transition dynamics.

2. The Role of Hybrid Technologies in the Diffusion of Innovations

When a technological discontinuity occurs, such as the introduction of new technology or that repackaging of technologies that disrupt the existing technological regime, a period of ferment unfolds in which technologies compete to become the new dominant design (Anderson and Tushman 1990; Utterback 1996). Radical technologies often face bottlenecks in their early days that could impede consumer adoption. Hybridization with the established technology can be an effective strategy to overcome these bottlenecks (Geels 2002). For example, hybrid sailing ships that incorporated elements of steam ships, such as steam propulsion and iron hull frames, were integral in developing the competencies needed to transition to build effective steam ships, discussed in greater detail below. In the automotive market, HEVs implement the fundamental elements of a BEV: an electric motor and a battery for electricity storage, but overcome some fundamental limitations of early BEVs, utilizing the existing gasoline infrastructure for fuel, generating electricity on-board through regenerative braking, and only require a small battery, minimizing the cost of this expensive component. The complementary attributes of the gasoline and electric powertrains provide a significant improvement in fuel economy over the conventional gasoline vehicle, while maintaining the long range provided by gasoline fuel without the need for a ubiquitous recharging infrastructure. Here I explore the complementary and competitive relationships that exist between HEVs and more radical EV platforms.
**Hybrids as a Transitional Technology**

The dominant perspective in the technology strategy literature states that hybrids are a transitional technology, helping to achieve the breakthrough of radical technologies. During a period of technological ferment, it is assumed explicitly (Utterback 1996) or implicitly (Klepper 1996) that a general progression towards the new dominant design unfolds, in which superior technologies emerge incorporating the components of earlier inferior technologies. By definition, hybrid technologies build on the dominant design, incorporating features of radical alternatives, accumulating experience and complementary assets that may spill over and help bring the radical technology to market. Manufacturers experience learning-by-doing through the efficiency gains and micro-innovations that occur with repeated production (Arrow 1962). However, this knowledge may not be fully appropriated by the hybrid technology. Product and process improvements can spillover to related technologies (Jovanovic and Lach 1989), through the use of shared components, reverse engineering and the mobility of workers between firms. Consumers accumulate familiarity with the hybrid technology from first-hand experiences discussing hybrid technologies with friends and observing the hybrid technology in use (Struben 2006). As with producer learning, this knowledge may spillover to the radical technology, to the extent that the attributes of the hybrid technology are shared with the radical technology. Familiarity spillovers were observed as far back as the initial platform competition in the automotive market at the start of the 20th century. When the electric starter motor was developed for the internal combustion engine by Charles Kettering in 1910 (Pound 1934), overcoming the need to hand crank start, gasoline vehicles were sometimes referred to as 'electrified gas' vehicles, noting the similarity between the gasoline vehicle and the competing electric vehicle of the day (Kirsch 2000). Third, consumer adoption of the hybrid technology builds complementary assets such as component supply chains, dealer networks and aftermarket service capability, benefiting the radical technology to the extent that these complementary assets are mutually compatible.

A seminal example of hybrids in the technological transition is the shift from sailing ships to steamships through the 19th century, described by Geels (2002). In the late 18th century, protectionism in the British-dominated shipping industry favored large, slow ships, because cargo capacity was considered more important than speed. In the early 19th century, speed became an increasingly important attribute, as traders, merchants and passengers sough more regular and reliable transportation. Steamships had an inherent appeal for faster travel, not dependent on
favorable winds. However, early steamships were small wooden vessels that used low-pressure steam engines and paddlewheels, which had numerous drawbacks. Steamers needed to carry coal on board, which limited the capacity remaining for freight, and paddlewheels were not always effective in rough seas. Two important innovations in the 1830s overcame these limitations. First, screw propulsion was demonstrated, and second, higher boiler pressure improved the efficiency of coal use. However, each of these innovations created their own problems. The vibrations created by screw propulsion caused wooden ships to shake apart, while the heavier boilers needed to withstand higher pressures caused wooden ships to warp and bend. At the same time, some shipbuilders began experimenting with iron ships. Iron ships had the potential to be stronger and lighter than wooden ships. However, using the same design criteria used for wooden ships made these early steamships unstable, sometimes overturning upon their launch, and they required new metalworking skills not possessed by existing shipbuilders. The breakthrough for iron occurred in the 1850s when 'hybrid' sailing clippers were built, combining an iron frame with wooden planking to make ships that employed the complementary attributes of iron and wood. Insurance premiums for iron ships dropped, and transatlantic transport of passengers became a niche for steamships, and the transformation of an industry to iron steamships had commenced, which would play out over the following decades. Geels (2002) provides three explanations for why the transition to iron steamships was gradual: First, the accumulation of experience led to better boiler, lubricant and steel technologies, which increased the attractiveness of steamships. Second, defensive strategies from the sailing ship industry led to new innovations that prolonged market share, such as labor-saving rigging machinery and adding additional masts, the so-called 'sailing ship effect'. Third, the reconfiguration of the shipping industry took time. Ports needed to be widened and deepened to accommodate larger steamships. New cargo-handling infrastructure was required to facilitate the rapid turnaround of these faster ships. And, finally, shipbuilders needed to acquire the skills and machinery needed to manufacture new iron steamships. In this example, finding a niche market for a hybrid technology facilitated the accumulation of experience and infrastructure needed for the radical technology to flourish.

In the automotive market, the best contemporary example of the transitional role for hybrid technology may be Toyota's leverage of the iconic Prius HEV to create the Prius Plug-In PHEV, scheduled for introduction in Spring 2012. The Prius Plug-In PHEV uses the same body and powertrain as the current model Prius HEV, adding a 4.4kWh lithium-ion battery to provide sufficient electricity for an estimated 14.3 mile all-electric range, and a recharging port to allow recharging directly from the electricity grid. To be produced in the same Tsutsumi (Japan) plant as
the Prius HEV, the Prius Plug-In PHEV will benefit from the production experience and component supply chains that Toyota has developed over the past decade. In the marketplace, consumers will immediately recognize the Prius PHEV as a derivative of the classic Prius HEV, emphasized in Toyota's marketing of the 'Prius Family', essentially elevating Prius as a sub-brand of Toyota.

**Hybrids as a Medium-Term Barrier**

The HEV can only ever be a transitional technology. It remains powered by non-renewable fossil fuel, so must eventually be replaced by a technology powered by renewable, carbon-neutral energy. Even if a drop-in renewable liquid fuel became available, however, HEVs will remain more expensive than conventional internal combustion engine (ICE) vehicles because they require an ICE engine and additional electric drive and battery components. Despite this, each of the AFV technologies currently under development have significant barriers to overcome to become commercially viable, suggesting the HEVs may yet have an important role to play in achieving energy and environmental goals for the foreseeable future. Barriers to electric vehicle adoption including high battery costs, low energy density that limits vehicle range, and long recharging times (Simpson 2006; Kromer 2007; Lemoine, Kammen et al. 2008). Hydrogen fuel cells have been plagued by similarly high costs and poor durability, and hydrogen (an energy carrier) cannot yet be made from renewable energy at reasonable cost (Farrell, Keith et al. 2003; National Research Council 2004; Sperling and Ogden 2004; Romm 2006). Ethanol is more compatible with existing internal combustion engines, but the greenhouse gas emissions benefit from corn ethanol compared with gasoline are thought to be negligible or even negative (Farrell, Plevin et al. 2006; Searchinger, Heimlich et al. 2008). Each of these vehicles also lacks the ubiquitous distribution and refueling infrastructure needed to make driving and refueling as convenient as conventional gasoline vehicles are today.

The 'transitional technology' theory discounts the possibility that the hybrid technology may slow the transition to the radical entrant technology. The transitional technology theory relies on the producer experience, consumer familiarity and complementary assets accumulated by the hybrid technology spilling over to the radical technology, creating an ecosystem in which the radical technology is embraced. The product lifecycle also implies that the hybrid technology rapidly exits the market once the radical technology has entered the market and forms the new dominant design. However, various mechanisms exist by which the hybrid technology could come to form a barrier in the technological transition. First, limited, slow or incomplete spillovers from the hybrid technology to the radical technology could prevent the radical technology from
succeeding. Second, the hybrid technology might not develop a key capability needed by the radical technology, such as the refueling infrastructure needed by alternative fuel vehicles. Third, the spill over of capabilities need not only from the hybrid technology to the radical technology; the introduction of the radical technology could develop capabilities that spill back to the hybrid technology, reinforcing the hybrid regime. Fourth, firms have limited resources, and development of a hybrid technology may limit the resources available to develop the related radical technology.

In the automotive market, the extent to which spillovers occur between platforms is an open question. Spillovers can occur in various aspects of the automotive technology diffusion, including cost-reductions that result from producer learning and R&D, the accumulation of consumer familiarity and in growing demand for new refueling infrastructure. At the technological level, HEVs share components with the PHEV and BEV platforms, including traction batteries, electric motors and power electronics. However, at the firm level, these components are not identical. For example, while the battery manufactured in-house for the Nissan Leaf BEV relies on passive thermal management, the battery for the Chevrolet Volt PHEV, sourced from LG Chem, uses a liquid coolant for active thermal management. As a result, experiences from the PHEV platform are unlikely to spill over fully to the BEV platform. Further, at the system level, experience gained in powertrain integration is not equally valuable across platforms. For example, the ability to effectively control a hybrid gasoline-electric powertrain, as developed in the HEV and PHEV platforms, has no value to the fully electric BEV platform. For consumers, familiarity with a new technology is crucial if it is to be included in the consumers’ consideration set. Prior research on the diffusion of the Toyota Prius HEV (see Essay 1 and Essay 2) demonstrates that consumer acceptance of expensive and complex powertrain technologies is gradual, accumulated through social exposure to marketing and word-of-mouth. The existence of multiple competing but related technologies is likely to make understanding the similarities and differences between these technologies more challenging, reflected in consumers’ confusion about the specific attributes of particular platforms in a market research survey (Ipsos 2011). With most automakers backing a single hybrid or electric platform to date, few incentives exist for firms to design or market vehicles in a way that facilitates the spillover of consumer familiarity across platforms. Finally, the co-evolution of refueling infrastructure is crucial for all alternative fuel vehicles facing the ‘chicken and egg’ infrastructure dilemma (Strubin and Sterman 2008), as only gasoline has a ubiquitous refueling infrastructure at present. However, while HEVs incorporate components from the electric powertrain, HEVs do not contribute to the build-up of recharging infrastructure that would benefit EV platforms, because HEVs refuel exclusively from the existing gasoline infrastructure.
From a competitive perspective, the sale of over 2 million HEVs is evidence of considerable consumer appeal. HEVs are already available in a range of makes and models, satisfying a range of heterogeneous consumer preferences, and are widely recognized as signaling a preference for environmental sustainability. HEVs also have a considerable economic advantage relative to PHEVs and BEVs at the current price of oil and batteries. As with other energy-efficient technologies such as compact-fluorescent light bulbs and thermal insulation, hybrid and electric vehicles promise lower operating costs but come at a higher initial purchase price. Attributes of vehicles from the 2012 US Model Year representative of the GAS, HEV, PHEV and BEV platforms are shown below (Table 1), along with the financial payback associated with various cross-platform vehicle purchase decisions, calculated using the gasoline-equivalent fuel economy for simplicity (Table 2):

**Table 21: Economic Attributes of Representative Vehicles**

<table>
<thead>
<tr>
<th>Platform</th>
<th>Representative Make/Model</th>
<th>Manufacturer’s Suggested Retail Price ($)</th>
<th>Fuel Economy (miles per gallon - combined)</th>
<th>Operating Cost (cents per mile with $3.50/gallon gas)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAS</td>
<td>Toyota Matrix</td>
<td>$18,845</td>
<td>29</td>
<td>12.1</td>
</tr>
<tr>
<td>HEV</td>
<td>Toyota Prius</td>
<td>$24,000</td>
<td>50</td>
<td>7.0</td>
</tr>
<tr>
<td>PHEV</td>
<td>Chevrolet Volt</td>
<td>$39,145*</td>
<td>94^</td>
<td>3.7</td>
</tr>
<tr>
<td>BEV</td>
<td>Nissan Leaf</td>
<td>$35,200*</td>
<td>99^</td>
<td>3.5</td>
</tr>
</tbody>
</table>

* Prior to federal tax savings of up to $7,500

^ EPA ‘miles per gallon-equivalent’ rating for electric vehicles

**Table 22: Economic Implications of Cross-Platform Purchase Decisions**

<table>
<thead>
<tr>
<th>Purchase Decision</th>
<th>Incremental Purchase Price ($)</th>
<th>Operating Cost Saving (cents/mile)</th>
<th>Payback Period at 8% discount rate (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAS -&gt; HEV</td>
<td>$5,155</td>
<td>5.1</td>
<td>14.6</td>
</tr>
<tr>
<td>GAS -&gt; PHEV</td>
<td>$20,300</td>
<td>8.4</td>
<td>100+</td>
</tr>
<tr>
<td>GAS -&gt; BEV</td>
<td>$16,355</td>
<td>8.6</td>
<td>100+</td>
</tr>
<tr>
<td>HEV -&gt; PHEV</td>
<td>$15,145</td>
<td>3.3</td>
<td>100+</td>
</tr>
<tr>
<td>HEV -&gt; BEV</td>
<td>$11,200</td>
<td>3.5</td>
<td>100+</td>
</tr>
</tbody>
</table>

For drivers of a conventional gasoline vehicle, the HEV is the most economically attractive of the available hybrid and electric vehicle alternatives for most reasonable discount rates. For drivers who have already purchased an HEV, neither of the PHEV or BEV platforms provides an
economic payback on the incremental purchase price required to make an economic justification for adoption of those platforms.

3. Model Formulation

Here I develop a simulation model that formalizes the platform competition dynamics described above, summarized in Figure 27. Consumer choice is modeled as a nested discrete choice between 'liquid fuel' and 'plug-in' vehicle types, where the utility of each vehicle platform is a function of attributes such as purchase price, operating cost, vehicle range and greenhouse gas emissions. Familiarity is modeled as a resource that consumers accumulate with each of those vehicle platforms, based on exposure to marketing and to word-of-mouth arising both from drivers of each particular vehicle platform. Familiarity can spill over between platforms, when exposure to a platform also educates a consumer about a different, related platform. Learning-by-doing is modeled at the vehicle system level, capturing both the accumulation of production experience within each platform’s systems, and the spillover of this experience to other platforms' systems. Finally, refueling infrastructure coevolves in response to utilization of the available infrastructure by the installed base of each vehicle platform. This model is formulated as a series of coupled nonlinear differential equations, for which results are derived using simulation. In the scenario analysis, the model is parameterized to represent the light vehicle market in the United States.
3.1. Consumer Choice

Consumers choose their vehicle based on their perception of the utility of the four available vehicle platforms: GAS, HEV, PHEV and BEV. It is assumed that consumers use a two-stage decision-making process, representing using a nested multinomial logit (NMNL) structure (Train 2009). First, they choose between a liquid fuel vehicle (GAS & HEV) and a plug-in vehicle (PHEV & BEV). Second, they choose between the available vehicles within that category, as shown in Figure 1:

![Vehicle Choice Decision Structure](image)

The market share of drivers of platform $i$ choosing platform $j$ is calculated as the share of platform $j$ within its nest, multiplied by the market share of platform $j$'s nest compared with other nests. For example, the probability of a driver of platform $i$ choosing the HEV platform, $P(HEV)$ is given by:

$$P(HEV) = P(HEV | LF) \times P(LF)$$  \hspace{1cm} (1)

The probability of choosing the Liquid Fuel Vehicle nest, $P(LF)$, is:

$$P(LF) = \frac{e^{I_i / \lambda}}{e^{I_i / \lambda} + e^{I_n / \lambda}}$$  \hspace{1cm} (2)
where \( \lambda \) is a measure of the independence in unobserved utility for alternatives in the same nest, \( I_{LF} \) is the ‘inclusive value’ for the Liquid Fuel nest, and \( I_{PI} \) is the inclusive value for the Plug In nest, given by:

\[
I_{LF} = \ln(e^{u_{\text{GAS}/\lambda}} + e^{u_{\text{HEV}/\lambda}}) \quad I_{PI} = \ln(e^{u_{\text{PHEV}/\lambda}} + e^{u_{\text{BEV}/\lambda}})
\]

where \( u_{ij} \) is the expected utility of platform \( j \) as perceived by drivers of platform \( i \), as described in Essay 1. The expected utility of a technology depends on both the utility of that vehicle and the extent to which a customer is familiar with that technology such that they are willing to consider that technology on its merits:

\[
u'_{ij} = u_{ij} \times F_{ij}
\]

where \( F_{ij} \) is the level of familiarity drivers of technology \( i \) have with technology \( j \). The probability of choosing the HEV platform within the LF nest is:

\[
P(\text{HEV} \mid LF) = \frac{e^{u'_{\text{HEV}}}}{e^{u'_{\text{GAS}}} + e^{u'_{\text{HEV}}}}
\]

The utility of vehicle platform \( j \) for drivers of platform \( i \), \( u_{ij} \), is a function of the observable technological attributes of the vehicle and demographic attributes of the driver:

\[
u_{ij} = \sum_k \beta_k \chi_{ij,k} + \varepsilon_{ij}
\]

where \( \beta_k \) represents the preference of consumers for vehicle attribute \( k \), \( \chi_{ij,k} \) is a matrix of observed attributes \( k \) for drivers of platform \( i \) considering vehicle platform \( j \), and \( \varepsilon_{ij} \) represents unobserved attributes and idiosyncratic consumer preferences that drivers of platform \( i \) hold for vehicle platform \( j \).
3.2. Scope of Platform Models Available

As demand for the new platform grows, OEMs scale up production and introduce new models until the platform is available in all market segments. This feedback is represented as an attribute of platform utility, negatively influencing the market share of new platforms in their early years. The effect of scope on platform utility, \( \psi_j \), is estimated as:

\[
\psi_j = -\frac{\beta_{PV}}{1 + e^{\gamma (S_j - S^*)}} + \beta_{PV}
\]  

(7)

where \( \beta_{PV} \) is the effect of product scope on consumer utility, \( \gamma \) is the sensitivity of OEM product scope to cumulative sales, \( S_j \) is the cumulative number of sales of platform \( j \), and \( S^* \) is the reference level of cumulative sales. This function takes the logistic form demonstrated in Figure 29, which can be parameterized to vary the effect of scope on utility and the sensitivity of scope to cumulative sales.

Figure 29: Example Scope Function (\( \Psi = -0.5 \), Sensitivity = 10)

3.3. Fleet Turnover

Approximately 240 million light vehicles are registered in the United States. Only a small fraction of this fleet turns over each year, as vehicles are retired due to aging and car crashes. New
vehicle sales replace these retired vehicles in the fleet. A fully specified fleet model might use 1-year age cohorts with age-specific hazard rates of replacement. This level of detail is not needed to understand the fundamental fleet turnover dynamics. However, the simplest possible model of the fleet involving a single stock lacks sufficient detail, failing to recognize that new vehicles (including sales of new platforms) almost always remain in the fleet for several years, except when they are involved in crashes. Here I use a two stock model of the vehicle fleet, comprising Newer Vehicles aged 0-5 years, and Older Vehicles more than 5 years old. As in Essay 1, the stock of Newer Vehicles is given by Dealer Vehicle Sales less Newer Vehicle Aging and Newer Vehicle Retirements:

\[
\frac{dQ_i}{dt} = s_j - \omega Q_j - \frac{Q_i}{\tau_a}
\]  

(8)

where \(\omega\) is the fraction of Newer Vehicles retired prematurely each month due to crashes and breakdowns, and \(\tau_a\) is the vehicle aging time constant. The stock of Older Vehicles increases with Newer Vehicle Aging and decreases with Older Vehicle Retirements:

\[
\frac{dU_j}{dt} = \frac{Q_i}{\tau_a} - \frac{U_i}{\tau_r}
\]  

(9)

where \(\tau_r\) is the used vehicle aging time constant. The fraction of new vehicle buyers who currently drive vehicle platform \(i\) is the weighted fraction of platform \(i\) drivers from the fleets of Newer and Older Vehicles:

\[
q_i = k \left( \frac{Q_i}{\sum Q_i} \right) + (1-k) \left( \frac{U_i}{\sum U_i} \right) \quad i \in x
\]  

(10)

where \(k\) is the fraction of vehicle sales that come drivers who currently own New Vehicles. The model does not explicitly represent the dynamics of the used vehicle market. I argue this approach is sufficient given the simple aging chain structure used and the lack of detail regarding market segments. However, incorporating the used vehicle market is an important opportunity for future work, as the used vehicle market is a balancing feedback that can extend the life of conventional gasoline vehicles. Aggressive adoption of hybrid and electric vehicles could flood the used vehicle market.
market, driving down used vehicle prices and attracting consumers to buy gasoline vehicles from the used vehicle market (Struben and Sterman 2008). This feedback loop has been identified as a place for high-leverage policy interventions, using instruments such as ‘Cash for Clunkers’ incentives and feebate schemes (Ford 1995; Greene, Patterson et al. 2005; Zolnik 2012).

3.4. Consumer Familiarity and Familiarity Spillovers

As in Essay 1, consumers are assumed to possess a stock of familiarity with each vehicle platform, capturing 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 2006). All drivers possess full familiarity with the conventional gasoline vehicles, to $F_{i,GAS} = 1$. For all other vehicle platforms $j$, so $F_{ij} = 0$ when a new platform is first introduced. Consumer familiarity with platform $j$ among drivers of platform $i$ increases with social exposure to platform $j$, and erodes through forgetting:

$$\frac{dF_{ij}}{dt} = z_j (1 - F_{ij}) - \phi F_{ij}$$

where $z_j$ is the aggregate effect of social exposure, and $\phi$ is the fractional rate of forgetting. Social exposure to platform $j$ is the sum of three factors: (i) the effect of marketing, $z_{jm}$, (ii) the effect of word-of-mouth from drivers of platform $j$, $z_{jd}$, and (iii) the sum of socialization that spills over from drivers of all other platforms, $z_{dk}$:

$$z_j = z_{jm} + z_{jd} + \sum z_{jk} \forall k \neq j$$

The socialization effect of marketing is determined by the level of marketing spending on platform $j'$, $m_j$, and the effectiveness of marketing spending, $e_m$:

$$z_{jm} = e_m \times m_j$$

The socialization effect of word-of-mouth from drivers of a vehicle belonging to platform $j$ depends on the effective contact rate of word-of-mouth between vehicle drivers, and the probability that a

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contact will occur between other drivers and a driver of a vehicle of platform \( j \). Following standard diffusion models, that probability is given by the fraction of platform \( j \) vehicles in the total vehicle fleet:

\[
Z_j^d = ecr_t \times \left( \frac{N_j}{N_t} \right)
\]  

(14)

If different platforms, \( j, k \), share basic product architecture and components, then it is possible that exposure to platform \( k \) may spill over and increase consumer familiarity with platform \( j \). For example, familiarity with conventional HEVs such as the Prius may increase consumer familiarity with PHEVs such as the Plug-in Prius, or even BEVs such as the Nissan Leaf. Spill over socialization to platform \( j \) arising from drivers of vehicles belonging to platform \( k \), \( z^w_{jk} \), is formulated analogously to driver word-of-mouth as depending on the effective contact rate between vehicle drivers and the probability that a contact will occur between other drivers and a driver of a vehicle of platform \( k \), adjusted by the extent to which word-of-mouth from platform \( k \) spills over to platform \( j \), \( \delta_{jk} \):

\[
Z_{jk}^w = \delta_{jk} \times ecr_t \times \left( \frac{N_k}{N_t} \right)
\]  

(15)

The spill over coefficients \( \delta_{jk} \) will depend on the extent to which consumers perceive that the different platforms are similar. These in turn should depend on actual similarity, as determined by the extent of shared designs and components, but are also dependent on the ways consumers perceive and categorize different vehicles, which in turn may be affected by marketing.

### 3.5. Technological Improvement from Producer Learning-by-Doing and R&D

Technological improvement, realized as cost-reductions in vehicle components, result from learning-by-doing in production and investments in research and development (R&D). Technological improvement as a result of producer economies-of-scale and learning-by-doing is represented using a standard power-law learning curve (Argote and Epple 1990) in cumulative experience. Technological improvement as a result of R&D investment is also represented using a standard power-law learning curve in cumulative R&D spending. Technological improvement is
represented separately in four different vehicle subsystems: 1) the vehicle 'glider' (chassis, body, interior, exterior, wheels and suspension); 2) the gasoline powertrain (engine and transmission); 3) the electric powertrain (motor, regenerative brakes, wiring and on-board recharger) not including the battery; and 4) the traction battery, used to store electricity in hybrid and electric vehicles.

The performance, $P$, of vehicle subsystem $h$ within each platform $j$ improves with experience and R&D:

$$P_{jh} = P_{jh}^0 \left[ 1 - \omega_e \left( 1 - \frac{E_{jh}}{E_{jh}^0} \right)^{\gamma_e} \right] \left[ 1 - \left( 1 - \omega_e \right) \left( 1 - \frac{RD_{jh}}{RD_{jh}^0} \right)^{\gamma_{RD}} \right]$$

(16)

where $E_{jh}$ is the current level of experience with subsystem $h$ in platform $j$, $E_{jh}^0$ is the reference level of experience with subsystem $h$ in platform $j$, $P_{jh}^0$ is the price of subsystem $h$ at the reference level of experience, $\gamma_e$ is the strength of the experience learning curve and $\omega_e$ is weight placed on learning from experience versus R&D by manufacturers, while $RD_{jh}$ is the current level of R&D with subsystem $h$ in platform $i$, $RD_{jh}^0$ is the reference level of R&D with subsystem $h$ in platform $j$ and $\gamma_{RD}$ is the strength of the R&D learning curve. As is common in studies of producer learning, cumulative production is used as a proxy for the aggregate effect of all sources of learning, while performance is measured in terms of cost.

The total production experience that accumulates with platform $j$ is the sum of direct production experience with platform $j$ and spillovers of production experience from all other platforms $k$ that employ the same vehicle subsystem:

$$\frac{dE_{jh}}{dt} = (s_j + \nu_h \sum \theta_{jk}^h) \cdot \theta_{jh} \quad \forall k \neq j$$

(17)

where $\nu_h$ is the extent of producer experience spillovers that occur between platforms in subsystem $h$, $\theta_{jh}$ is the fraction of platform $j$'s total investment in technological change spent on learning, and $\theta_{jh}$ is the share of that learning investment spent on subsystem $h$. The extent of spillovers is governed by factors such as industry structure and employee mobility. $\nu = 0$ implies that each platform is manufactured by a different firm using its own proprietary and perfectly appropriable component technologies, preventing spillovers. $\nu = 1$ implies that multiple platforms are
manufactured by a single firm or by firms using a common component supplier for different platforms, or that firms or their suppliers can use reverse engineering or other forms of knowledge transfer to benefit from improvements achieved in other platforms, enabling full spillovers.

The total R&D spending that accumulates with platform \( j \) is the sum of direct R&D investment in platform \( j \) and spillovers of R&D investment from all other platforms \( k \) that employ the same vehicle subsystem:

\[
\frac{dRD_{jh}}{dt} = \left( r_{j}^{RD} + v_{h} \sum r_{k}^{RD} \right) \theta_{jh}^{RD} \quad \forall k \neq j
\]

where \( r_{j}^{RD} \) is the amount of platform \( j \)'s revenue spent of R&D (equal to \( 1 - \theta_{j} \) of the total investment in technological change), \( v_{h} \) is the extent of R&D spillovers that occur between platforms in subsystem \( h \), and \( \theta_{jh}^{RD} \) is the share of that R&D investment spent on subsystem \( h \). For both learning and R&D, the allocation of resources between learning and R&D, and the allocation of effort between vehicle subsystems, is undertaken on the basis of the marginal return on investment in each subsystem.

### 3.6 Infrastructure Co-Evolution

The availability of refueling infrastructure is a critical determinant in the success or failure of alternative fuel vehicles (Yeh 2007; Struben and Sterman 2008). Without readily accessible refueling infrastructure, an alternative fuel vehicle holds little appeal to consumers. The four vehicle platforms considered in this study refuel from two distinct infrastructures: 1) the ubiquitous gasoline station infrastructure that currently exists in the United States; and 2) the nascent electricity recharging point infrastructure being deployed by private developers and initiative such as The EV Project (The EV Project 2012). Fuel infrastructure availability strongly conditions consumer vehicle choice, and in turn alternative fuel demand arising from consumer purchasing and driving choices affects the incentives to build refueling infrastructure, forming an important feedback process that conditions the evolution of alternative fuel vehicles. Note: I use the terms 'infrastructure' and 'fuel' interchangeably, and I use the term 'fuel' generically to mean both gasoline and electricity.

The total number of fuel stations available for each infrastructure, \( T_{h} \), accumulates new station installations, \( T_{i}^{h} \), less retirements, \( T_{r}^{h} \):
Station installations and retirements depend on the financial viability of refueling stations, influenced by factors including site costs, feedstock and labor costs, fuel sales and ancillary sales such as food and drinks, which vary widely by geographic location (Supple 2007). Here I abstract away from these details, using a single variable to represent fuel station viability: the rate of station utilization. New stations of infrastructure \( f \) enter the market at the rate:

\[
\frac{dT^I_f}{dt} = t^p_f - t^I_f
\]  

(19)

when \( T^\Delta_f \) is positive, where \( T^\Delta_f \) is the desired change in infrastructure \( f \) and \( \tau_n \) is the time to plan and install new stations. The desired change in infrastructure \( f \), \( T^\Delta_f \), is calculated based on the gap between the projected level of utilization given the recent state of the market, \( \mu_f^p \), and the target level of utilization, \( \mu^*_f \):

\[
T^\Delta_f = T_f \left( \mu_f^p - \mu^*_f \right)
\]  

(21)

Stations are retired both at the end of their useful life and when they are being under-utilized (i.e. when \( T^\Delta_f \) is negative). The rate of station retirements is the greater of the rate of retirements from utilization and retirements from aging:

\[
t^I_f = \max \left( \frac{T^\Delta_f}{\tau^I_f}, \frac{T_f}{\tau^I_f} \right)
\]  

(22)

where \( \tau_r \) is the time to locate and decommission stations due to under-utilization, and \( \tau^\Delta_f \) is the average lifetime of stations of infrastructure \( f \). Infrastructure developers are assumed to make investment decisions based on the projected level of infrastructure utilization, because in a growing market, it is assumed that developers will build infrastructure based on their projection of future
utilization, even if the current level of utilization is below the target level needed for profitability. The projected level of utilization for infrastructure \( f \) is calculated as:

\[
\mu_f^p = \text{MAX}(0, \text{MIN}(1, \mu_f^r \times (1 + (g_f \times \tau_h))))
\]  

(23)

where \( \mu_f^r \) is the recent rate of utilization of infrastructure \( f \) as perceived by infrastructure developers, \( g_f \) is the expected rate of growth in utilization of infrastructure \( f \), and \( \tau_h \) is the time horizon used for forecasting, bounded between 0 and 1. The expected growth in utilization for infrastructure \( f \) is the exponential smoothing of the indicated utilization growth rate for infrastructure \( f \), \( g_f' \), with smoothing time \( \tau_p \). The indicated utilization growth rate for infrastructure \( f \) is the average fractional growth rate of infrastructure utilization over the historic time horizon for infrastructure growth, \( \tau_g \). The recent level of utilization is calculated as an exponential smoothing of the current level of utilization of infrastructure \( f \), \( \mu_f \), with smoothing time \( \tau_p \) equal to the infrastructure utilization perception time. The current level of utilization of infrastructure \( f \), \( \mu_f \), is calculated as total station demand for infrastructure \( f \), \( T_f \), divided by the available number of stations for infrastructure \( f \), \( T_f' \):

\[
\mu_f = \frac{T_f}{T_f'}
\]  

(24)

Demand for refueling infrastructure varies by platform, according to the powertrain technology employed. Both the GAS and HEV platforms refuel exclusively from gasoline stations. For plug-in EVs (PHEVs and BEVs), I distinguish between private and public recharging. First, I assume that all EV buyers install a recharging point at home, including the cost of the recharging point in the purchase price of the vehicle. I also assume that EV drivers recharge their vehicle overnight every night. The percentage of platform \( j \)'s vehicle miles traveled that are satisfied by private recharging is a function of platform \( j \)'s electric range and the distribution of daily VMT. Daily VMT is assumed to follow a gamma distribution, parameterized using data from the 2001 National Household Transportation Survey (Lin and Greene 2010). The electric fraction of total VMT for a given electric range can be derived from the distribution of daily vehicle distance, as described in SAE standard J2841 (Society of Automotive Engineers 2010), which assumed that
PHEVs are fully recharged each and every evening. For days where the distance traveled is less than the electric range of the PHEV, 100% of miles travelled are assumed to occur in electric vehicle. For days where the distance traveled is greater than the electric range of the PHEV, the electric range of the PHEV is depleted first, and the balance of miles are fueled using gasoline. Both the gamma distribution of daily vehicle distance and the derived electric fraction of total VMT for a given PHEV electric range are shown in Figure 30:

![Figure 30: Cumulative Distribution Function - Daily VMT and % Electric Miles](image)

When a BEV is driven further in a single day than the electric range achieved from home recharging (less the safety margin the driver desires), recharging from public infrastructure is required. When a PHEV is driven further in a single day than the electric range achieved from home recharging, the driver can choose to recharge from public infrastructure, or continue driving using gasoline fuel. The decision to fuel with gasoline or recharge is modeled as a binomial logit choice based on search distance and refueling (recharging) time. Assuming that a random quantity of gasoline remains in the tank when the PHEV battery is depleted, the driver may or may not need to refuel with gasoline at that time. However, I reduce this to a binary decision, because choosing to not recharge with electricity implies a preference for refueling with gasoline, whether immediately or in the future. These dependencies and decisions generate a map, \( \chi \), summarizing the share of annual vehicle miles traveled for a vehicle of platform \( j \), \( VMT_j \), which are fueled from each infrastructure \( f \).

The annual number of refuels per vehicle of platform \( j \) from infrastructure \( f \) is the number of miles traveled using each fuel, divided by the vehicle's effective range, \( r_{jf} \) (see Section 3.5):
\[ \omega_j = \frac{VMT_j \cdot X_j}{r'_j} \]  

(25)

The demand for refueling stations of infrastructure \( f \) from each individual vehicle platform \( j \) is the product of the number of refuels per vehicle per year, the number of pumps required to service that vehicle (given station up-time \( \tau_o \), the time required to fuel that vehicle \( \tau_f \) and the number of pumps at the station \( \eta_f \)) and number of vehicles of platform \( j \) that exist in the fleet:

\[ \hat{T}_{ij} = \omega_j \cdot \left( \frac{\tau_o}{\tau_f \cdot \eta_f} \right) \cdot N_j \]  

(26)

The total demand for refueling stations of infrastructure \( f \) is the sum of demand for infrastructure \( f \) from each individual vehicle platform \( j \):

\[ \hat{T}_f = \sum_j \hat{T}_{ij} \]  

(27)

### 3.7. Fuel Buffer and Refueling Cost

Drivers maintain a 'fuel buffer', reducing the effective range of their vehicle, because searching for a refueling station requires driving, and running out of fuel is costly (such as waiting for roadside assistance or towing the vehicle to a refueling station). Drivers of all platforms maintain fuel buffers, for both gasoline and electricity, with one exception: I assume that PHEV drivers maintain a zero-mile buffer for electric miles, fully utilizing the vehicle's battery where possible, because of the backup provided by the gasoline engine. The effective range of platform \( j \) using fuel \( f \) is calculated as the nominal range, \( r^{\circ}_{jf} \), less the fuel buffer, \( \beta_{jf} \):

\[ r^{f}_{j} = r^{\circ}_{jf} - \beta_{jf} \]  

(28)

Drivers choose the optimal fuel buffer (in miles) that minimizes the effort required to refuel their vehicle, estimated at the total cost of refueling with fuel \( f \) at buffer \( \beta \):
\[ \beta_f = \arg\min_{\beta} (c^{\text{dist}}_f + c^{\text{cof}}_f + c^{\text{wait}}_f + c^{\text{service}}_f) \]  

(29)

where \( c^{\text{dist}}_f \) is the cost of driving to a refueling station of infrastructure \( f \) at buffer \( \beta \), \( c^{\text{cof}}_f \) is the cost associated with the risk of running out of fuel \( f \) at buffer \( \beta \) before finding a refueling station, \( c^{\text{wait}}_f \) is the cost of waiting in line to refuel from infrastructure \( f \) at buffer \( \beta \), and \( c^{\text{service}}_f \) is time cost of refueling from infrastructure \( f \) and buffer \( \beta \). The estimation of these costs implements the formulations developed by Struben (2006).

The annual cost of driving to a refueling station is a function of the number of refuels per year and the average distance from the driver's location to a refueling station. Because maintaining a larger fuel buffer initiates more refueling events, it also requires more driving to find refueling stations annually. The average distance to a refueling station, \(< r^d >\), is found by summing over the probability that the nearest refueling station is at distance \( r \) from the driver's current location, \( p^r_\beta \), multiplied by the distance:

\[ \langle r^d \rangle = \sum_{l=0}^{n} \frac{n!}{l!(n-l)!} r^l p^*_\beta \]  

(30)

equal to the probability that at least one station exists in ring \((r_l + dl)\) minus the probability that a station exists within ring \( r_l \) of the current location, \( p^l_\beta \):

\[ p^*_\beta = p^l_\beta - p^{l-1}_\beta \]  

(31)

The probability of finding at least one station within \( l \) is one minus the probability of not finding a station:

\[ p^l_\beta = 1 - p^0_\beta \]  

(32)

Assuming station locations exhibit spatial Poisson characteristics, the probability of not finding a station in ring \( l \) equals negative exponential of the density of stations multiplied by the area of ring \( l \):
\[ p_{i}^{0} = \exp \left( \frac{-T_i A_i}{A_{ss}} \right) \]  

where \( A_{ss} \) is the total area of the market and \( A_i = \pi((r_i + dl)^2 - r_i^2) \). The annual cost of driving to refueling stations, \( c_{\text{dist,}i} \), is the value of time needed to travel the average refueling distance each time the vehicle is refueled:

\[ c_{\text{dist,}i} = \langle r_f^d \rangle * \omega_f * \langle v \rangle * V_r \]

where \( \langle v \rangle \) is the driver's average speed (miles per hour) and \( V_r \) is the value of time.

The risk of running out of fuel increases as a driver maintains a smaller fuel buffer, because the likelihood of finding a refueling station within the action radius of the vehicle decreases. Here I assume that drivers decide deterministically to refuel exactly when they reach their fuel buffer, noting that in practice this decision is stochastic, because drivers may decide to opportunistically refuel early if they see a fuel station, or delay refueling if they have a pressing engagement. The expected risk of running out of fuel, \( < o_{of} > \), is estimated as:

\[ < o_{of} > = \frac{1}{1 + \left( \frac{\beta_{of}}{\langle r_f^d \rangle} \right)^{\eta}} \]

where \( \eta \) is the sensitivity of out-of-fuel probability to geographic infrastructure placement. The annual out of fuel risk cost is the expected value of time lost each year as a result of being stranded:

\[ c_{\text{oof}} = \langle o_{of} \rangle * \omega_f * \tau_{oof} * V_r \]

where \( \tau_{oof} \) is the time required to recover from an out of fuel event.

The dynamics of queuing introduces a paradox in relation to the utilization of refueling infrastructure: the high levels of utilization that create a financially viable market for infrastructure can also give rise to long waiting lists to access refueling infrastructure. Long lines appeared at US
gas stations during both 1970s oil shocks as nervous consumers rushed to fill their vehicles’ gas tanks (Sterman 2000). More recently, just the threat of a strike by gasoline tanker drivers over Easter 2012 was sufficient to trigger panic buying and long queues across the United Kingdom (Daily Mail 2012). Here I define station wait time as a function of infrastructure utilization, based on key reference points. When utilization of infrastructure \( f \), \( \mu_f \), is 0, average wait time \( \langle \tau^w \rangle \) is 0 also. When \( \mu_f \) equals the target utilization level, \( \mu_{f}^{*} \), \( \langle \tau^w \rangle \) equals the target wait time, \( \langle \tau^w_{f}^{*} \rangle \), by definition. Finally, as \( \mu_f \) approaches 1, \( \langle \tau^w_{f} \rangle \) approaches \( \infty \). Following this functional form, \( \langle \tau^w_{f} \rangle \) is estimated as:

\[
\langle \tau^w_{f} \rangle = \langle \tau^w_{f}^{*} \rangle \frac{1 - (1 - \mu_f)^{\alpha}}{(1 - \mu_f)^{\alpha} - 1} \left( \frac{\mu_f^{*}}{1 - \mu_f} \right)
\]

An example of this non-linear effect is shown in Figure 31. At the target level of utilization, the wait time is equal to the target wait time, in the order of minutes in practice. Once the level of infrastructure utilization exceeds the target level, wait time to access the infrastructure grows increasingly quickly, becoming prohibitively long as utilization approaches 1.

**Figure 31: Effect of Infrastructure Utilization on Wait Time**

The annual cost of waiting is the value of time spent waiting each time the vehicle is refueled:
Finally, the annual time cost of refueling the vehicle depends on the quantity of fuel required to refill the tank (battery). The time to service each vehicle, $\tau_{jf}$, is given by the quantity of fuel being supplied to the vehicle, calculated as the effective range of platform $j$ ($r_{jf}$) divided by the fuel economy of platform $j$ ($\phi_j$), the rate at which fuel is pumped (charged) by infrastructure $f$, $\sigma_f$, and the transaction time required for payment, $\tau_{payment}$:

$$\tau_{jf} = \frac{r_{jf}}{\phi_j \sigma_f}$$

(39)

The annual time cost of refueling is the value of time spent at the pump (plug) each time the vehicle is refueled:

$$c_{jf}^{\text{service}} = \tau_{jf} \omega_j V_t$$

(40)

4. Scenario Analysis

To explore the evolution of and interactions among different EV platforms I develop a series of scenarios representing different technology, policy and behavioral assumptions. First, I establish a baseline, simulating a market where only GAS and HEV platforms compete. I then expand the analysis, exploring the role that HEVs play in consumer adoption of the more radical PHEV and BEV platforms in the presence of different technology and policy assumptions.

4.1. Model Parameterization

The model developed here can be used to represent any nation or region and any number and combination of vehicle platforms. Here I calibrate the model to the size of the US light vehicle market with four competing platforms, with attributes generalized from representative vehicles in the 2012 model year (Toyota Matrix for the GAS platform, Toyota Prius for the HEV platform, Chevrolet Volt for the PHEV platform and Nissan Leaf for the BEV platform, noting that these vehicles are not all directly comparable):
Table 23: Vehicle Attribute Assumptions

<table>
<thead>
<tr>
<th>Platform</th>
<th>Battery (kWh)</th>
<th>Gasoline Tank (gallons)</th>
<th>Fuel Economy (mpg)</th>
<th>Energy Efficiency (Wh/mi)</th>
<th>Acceleration (0-30mph in seconds)</th>
<th>% All-Electric Trips</th>
<th>Electric Range (miles)</th>
<th>Total Range (miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAS</td>
<td>0</td>
<td>14</td>
<td>25</td>
<td>N/A</td>
<td>3.6</td>
<td>0</td>
<td>0</td>
<td>420</td>
</tr>
<tr>
<td>HEV</td>
<td>1</td>
<td>12</td>
<td>50</td>
<td>N/A</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>600</td>
</tr>
<tr>
<td>PHEV</td>
<td>16</td>
<td>9</td>
<td>45</td>
<td>0.2</td>
<td>3.5</td>
<td>69</td>
<td>40</td>
<td>445</td>
</tr>
<tr>
<td>BEV</td>
<td>24</td>
<td>0</td>
<td>N/A</td>
<td>0.2</td>
<td>3</td>
<td>100</td>
<td>80</td>
<td>100</td>
</tr>
</tbody>
</table>

Data Sources: (Chevrolet 2012; Nissan 2012; Toyota 2012; Toyota 2012)

To parameterize the platform utility function (Table 3), I use coefficient estimates from a leading empirical study of consumer choice in the automotive market by Brownstone, Bunch et al. (2000) (BB&T). I choose this study from other similar studies (such as Berry, Levinsohn et al. (2004) and Train and Winston (2007)) as it combines both revealed and stated preference estimates, and both gasoline and electric vehicles were included in the experimental design. In general, I use BB&T's combined/revealed coefficient estimates, on the basis that preferences revealed from actual purchase decisions should be more representative than stated preference estimates. One exception is the coefficient I use for the effect of greenhouse gas emissions on utility. BB&T reveal a positive coefficient for greenhouse gas emissions, implying that consumers are attracted to vehicles that have higher emissions, which is counter-intuitive. The authors suggest the emissions polarity may be explained by the correlation between emissions and other unobserved attributes of vehicles, such as performance and quality. BB&T also provide a stated preference estimate, which is negative, consistent with expectations, but which may be influenced by a hypothetical bias by survey respondents (Ajzen, Brown et al. 2004; Babbie 2009). Here I use the average of the revealed and stated greenhouse gas emissions coefficients, which takes a negative polarity consistent with expectations. I add two further attributes not specified by BB&T to the utility function. First, the cost of refueling is included as an incremental operating cost, calculated as the annual refueling cost per platform (Section 3.7) divided by the annual vehicle miles travelled. Second, the scope of models available is added to approximate the availability of platform models in different market segments (Section 3.2), parameterized based on the scope of models available in the HEV market since 2000. The resulting utility function for platform j is:
\[
\text{Utility}_j = \beta_1 \left( \frac{\text{PurchasePrice}_j}{\ln(\text{Income})} \right) + \beta_2 (\text{OperatingCost}_j) + \beta_3 (\text{Acceleration}_j) \\
+ \beta_4 (\text{TopSpeed}_j) + \beta_5 (\text{Emissions}_j) + \beta_6 (\text{RefuelingCost}_j) + \beta_6 (\text{Scope}_j)
\]

(41)

where \( \beta_n \) is the coefficient (weight) attached to each attribute of utility, assumed to take the values in Table 24 for the scenario analysis below:

**Table 24: Consumer Utility Function Coefficient Assumptions**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Units</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purchase Price / ln(Income)</td>
<td>$'000s / ln($'000s)</td>
<td>-0.361</td>
</tr>
<tr>
<td>Operating Cost</td>
<td>cents/mile</td>
<td>-0.170</td>
</tr>
<tr>
<td>Acceleration</td>
<td>0-30mph in seconds</td>
<td>-0.149</td>
</tr>
<tr>
<td>Top Speed</td>
<td>miles/hour</td>
<td>0.272</td>
</tr>
<tr>
<td>Greenhouse Gas Emissions</td>
<td>Dimensionless (emissions fraction relative to comparable gasoline vehicle)</td>
<td>-0.149</td>
</tr>
<tr>
<td>Cost of Refueling</td>
<td>cents/mile</td>
<td>-0.170</td>
</tr>
<tr>
<td>Scope of Models Available</td>
<td>Dimensionless (cumulative platforms relative to reference cumulative sales)</td>
<td>-0.500</td>
</tr>
</tbody>
</table>

Various other assumptions are required in the model, describing the vehicle fleet, vehicle costs, consumer demographics, consumer familiarity and energy and environmental accounting (Table 25). Key assumptions include: The real price of gasoline grows linearly between year 2000 and year 2050, while the price of electricity remains constant; Learning from production experience is applied to cost only at the vehicle subsystem level; A 10-year marketing program is undertaken when each new platform is introduced; A 10-year infrastructure development program is when each of the plug-in electric (PHEV & BEV) platforms are introduced; and Greenhouse gas emissions per platform are calculated on a lifecycle basis, including vehicle manufacturing, operations and retirement. The assumption that gas prices rise over time while electricity prices remain constant is justified as an assumption that will strongly favor the diffusion of electric vehicles, implying that no substitution possibilities exist between oil and other fuels used to
generate electricity. The complex dynamics that govern energy prices are considered outside the boundary of the model.

Table 25: Key Assumptions - All Scenarios

<table>
<thead>
<tr>
<th>Variable Type</th>
<th>Variable</th>
<th>Assumed Value</th>
<th>Data Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Fleet</td>
<td>Fleet Size (vehicles)</td>
<td>240,000,000</td>
<td>(BTS 2012)</td>
</tr>
<tr>
<td></td>
<td>Average Vehicle Lifetime (years)</td>
<td>15</td>
<td>(Goulding 2012)</td>
</tr>
<tr>
<td></td>
<td>Average Annual Vehicle Miles Traveled (miles)</td>
<td>12,000</td>
<td>(DOE 2012)</td>
</tr>
<tr>
<td></td>
<td>VMT Growth (%/year)</td>
<td>0%</td>
<td>Author assumption</td>
</tr>
<tr>
<td>Demographics</td>
<td>Household Income – Year 2000 ($/year)</td>
<td>40,000</td>
<td>(U.S. Census Bureau 2010)</td>
</tr>
<tr>
<td></td>
<td>Real Income Growth (%/year)</td>
<td>2%</td>
<td>Author assumption</td>
</tr>
<tr>
<td>Emissions and Cost</td>
<td>Emissions Factor – Gasoline (tonnes CO$_2$/gallon)</td>
<td>0.00892</td>
<td>(EPA 2012)</td>
</tr>
<tr>
<td>Accounting</td>
<td>Emissions Factor – Electricity [Grid Mix] (tonnes CO$_2$/MWh)</td>
<td>0.5883</td>
<td>(EPA 2012)</td>
</tr>
<tr>
<td></td>
<td>Emissions Factor – Electricity [Renewable] (tonnes CO$_2$/MWh)</td>
<td>0</td>
<td>Author assumption</td>
</tr>
<tr>
<td></td>
<td>Gasoline Price – Year 2000 ($/gallon)</td>
<td>$1.50</td>
<td>Author assumption</td>
</tr>
<tr>
<td></td>
<td>Gasoline Price – Year 2050 ($/gallon)</td>
<td>$4.00</td>
<td>Author assumption</td>
</tr>
<tr>
<td></td>
<td>Electricity Price – Grid Mix (cents/kWh)</td>
<td>11.09</td>
<td>(EIA 2012)</td>
</tr>
<tr>
<td></td>
<td>Electricity Price – Renewable (cents/kWh)</td>
<td>12.84</td>
<td>(NREL 2010)</td>
</tr>
<tr>
<td>Vehicle Cost</td>
<td>Base Vehicle Cost – Year 2000 ($)</td>
<td>$15,000</td>
<td>(Bandivadekar, Bodek et al. 2008)</td>
</tr>
<tr>
<td></td>
<td>ICE Engine Cost – Year 2000 ($)</td>
<td>$3,000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Electric Architecture Cost – Year 2000 ($)</td>
<td>$3,000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Unit Battery Cost – Year 2000 ($/kWh)</td>
<td>$1,000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Producer Markup</td>
<td>10%</td>
<td>Author assumption</td>
</tr>
<tr>
<td>Consumer Familiarity</td>
<td>Marketing Effectiveness (dmnl/$million)</td>
<td>0.00015</td>
<td>Calibration to HEV diffusion 2000-2010</td>
</tr>
<tr>
<td></td>
<td>Effective Contact Rate – Platform Drivers</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td></td>
<td>New Platform Marketing Expenditure ($/year)</td>
<td>$10,000,000</td>
<td>Author assumption</td>
</tr>
<tr>
<td></td>
<td>New Platform Marketing Duration (years)</td>
<td>10</td>
<td>Author assumption</td>
</tr>
</tbody>
</table>
4.2. Scenario 1: Base Case – GAS and HEV only

I begin the scenario analysis considering a base case in which plug-in electric vehicles never enter the market. In the year 2000 the HEV platform is introduced, representative of the US vehicle market for the period 2000-2010, generating the simulations shown in Figure 3. Sales of the HEV platform grow logistically, diffusing through the installed base of vehicles more slowly as the fleet turns over, caused by two key factors. First, consumer familiarity grows logistically, driven by the reinforcing word-of-mouth feedback from existing HEV adopters, making consumers more likely to include the HEV platform in their consideration set. Second, the utility of the GAS platform falls relative to the HEV platform over time, as rising gasoline prices drive up platform operating costs and provide greater economic return on the improved fuel economy of the HEV platform. The effect of production scale and scope are also manifest in the utility of each platform. Opportunities for learning by producers are greater in the new electric powertrain components of the HEV platform than in the mature GAS platform, so the price of the HEV platform falls more quickly over time. However, the electric powertrain components only comprise a modest fraction of the overall HEV platform costs (which still needs essentially all the components of the GAS platform), so the effect of this cost reduction on the price of the HEV platform is limited. As consumer demand for the HEV platform grows, so does the scope of product offerings made by manufacturers (i.e. HEVs available in more body styles and configurations), improving the overall utility of the HEV platform as more consumers are able to find an HEV that suits their needs. In this scenario, HEVs comprise 84% of new vehicle sales by 2050, and 60% of the installed base by 2050. As HEVs diffuse through the fleet, the average fuel economy of the fleet improves, reducing the volume of fuel required by the fleet, assuming constant fuel economy for each platform and constant vehicle miles traveled by each platform each year. As a result, fewer gas stations can operate profitably, and a co-evolutionary reduction in the number of gasoline stations in the United States is observed. Annual greenhouse gas emissions fall 26% below 2000 levels by 2050, also due to the reduction in gasoline consumption from the more efficient HEV platform.
Figure 32: GAS and HEV Only (Base Case)
4.3. **Scenario 2: Three Competing Platforms – GAS, PHEV and BEV**

Now I consider a counterfactual market that *does not* have the conventional HEV platform introduced in Scenario 1, but *does* have the more radical plug-in EV platforms. The market has three platforms, with the PHEV and BEV platforms entering the market in 2010. The purpose of Scenario 2 is to consider how successful the transition to the radical platform may be in the absence of the hybrid technology, of interest as I seek to establish the role that the presence of the HEV may make in helping or hindering this transition. It is important to reiterate that the market here is generally favorable to EVs. While the price of gasoline rises from $1.50/gallon in 2000 to $4.00/gallon in 2050, causing the operating cost of the GAS platform to rise from 6 cents/mile in 2000 to 16 cents/mile in 2050, electricity costs stay constant at 11.09 cents/kWh, giving the BEV platform an operating cost of 2.8 cents/mile. The PHEV and BEV platforms also enjoy purchase incentives of up to $7,500 for 10 years, and an infrastructure development program constructing 5,000 stations per year for 10 years. The simulation of this market is shown in Figure 33. Here the entrant PHEV and BEV platforms achieve logistic growth in sales, as the HEV platform did in the Base Case, driven by growing consumer familiarity and also considerable cost reductions with learning in EV traction batteries. However, two key differences are observed. First, competition between the PHEV and BEV platforms causes sales of both entrant platforms to share the market for plug-in vehicles, with the relatively more attractive PHEV platform achieving 77% of new vehicle sales by 2050. Second, consumer adoption of both the PHEV and BEV platforms is slower here than in the Base Case, because both these platforms are relatively more expensive than the HEV platform, and initially lack ubiquitous recharging infrastructure. Sales of the PHEV and BEV combined total approximately 12.7 million vehicles/year in year 2050 here, whereas HEV sales reached almost 13.4 million vehicles/year in year 2050 in the Base Case. With limited recharging infrastructure availability initially, refueling costs for the BEV platform are very high initially, due to the cost of searching for infrastructure until the market expands. After the 10-year infrastructure development program ends in 2020, the recharging infrastructure market falls, as insufficient demand exists create a financially viable infrastructure market, before a sustaining market with high utilization emerges after 2030. Assuming that the PHEV and BEV platforms recharge from the grid with its current mix of generation technologies, annual GHG emissions fall 22% below 2000 levels by 2050. The greening of the electricity grid or consumer adoption of green electricity would lead to even greater emissions reduction, as much as 38% below 2000 levels by 2050 if 100% renewable electricity is used for EV recharging.
Figure 33: Three Competing Platforms (Scenario 2)
4.4. Scenario 3: Four Competing Platforms – GAS, HEV, PHEV and BEV

Now I introduce the HEV platform into the market in 2000, and the PHEV and BEV platforms in the year 2010, creating a market with four competing platforms (Fig. 5), representative of the market that exists in the United States today. As in Scenario 2, I assume that no spillovers of technological learning or consumer familiarity exist, so the only interaction between the platforms is competition for market share. Here, the impact of competition between the hybrid and radical platforms is clearly evident: the HEV platform does worse than in Scenario 1 (no PHEVs and BEVs), and the PHEV and BEV platforms do worse than in Scenario 2 (no HEVs), even though total sales of all entrant platforms are greater than in either Scenario 1 or Scenario 2. With more platforms for consumers to choose from, the growth of the installed base on each entrant platform is slower, in turn slowing the rate at which consumers accumulate familiarity from word-of-mouth (in the absence of consumer familiarity spillovers between platforms) and also slowing the rate at which producers are able to achieve cost reductions through economies of scale and learning during production. However, this increased competition also accelerates the transition away from the GAS platform. Assuming that the PHEV and BEV platforms recharge from the electricity grid with the carbon intensity of the 2010 electricity generation mix, annual GHG emissions fall 28% below 2000 levels by 2050. Interestingly, if the PHEV and BEV platforms were recharged with 100% renewable electricity, emissions would fall 38% below 2000 levels, the same amount as in Scenario 2. That is, despite leading to fewer EVs being deployed, the presence of the HEV leads to the same or greater emissions reduction, suggesting that HEVs could help to achieve short-term environmental and energy policy goals, but may impede efforts to achieve a transition to carbon-free gasoline alternatives.
Figure 34: Four Competing Platforms (Scenario 3)

Vehicle Sales by Platform (vehicles/year)

Vehicle Installed Base by Platform (vehicles)

Annual GHGs (tonnes CO2-e/year)

Infr. Util. (dmnl) & Available Infr. (stations)

Consumer Familiarity with Platform (dmnl)

Platform Utility (dmnl)

Vehicle Price ($)

Platform Scope (dmnl)
4.5. Scenario 4: Vehicle cost-reduction spillovers

I now assume that the same four platforms compete in the market as in Scenario 2, but in addition, 100% of producer learning that occurs at the platform subsystem level spills over to all other platforms that share that subsystem (for example, if all EV manufacturers source components from the same supplier, causing the full spillover of product and process innovations among vehicle platforms). The purpose of Scenario 4 is to examine whether cost-reduction spillovers may alter the relationship between HEVs, PHEVs and BEVs described in Scenario 3. The simulation of this market is shown in Figure 35. In the presence of cost-reduction spillovers, improvements that lower vehicle component costs as a result of production experience and R&D investment in each entrant platform spill over to the other entrant platforms, accelerating the rate at which the other entrant platforms improve also. For example, it can be seen that the unit cost of PHEV and BEV batteries fall even before these platforms are introduced, due to the experience accumulated by the HEV platform in the period 2000-2010, which in turn reduce the overall price of each entrant platform, benefiting the most expensive BEV platform to the greatest extent. Why then is negligible difference observed in the trajectory of new vehicle sales for each platform? The answer lies in the timing of the benefits of cost-reduction spillovers. The additional experience gained from cost-reduction spillovers can be seen to be most beneficial when an entrant platform is in its infancy with few sales, and has yet to accumulate considerable experience itself. However, in practice, consumer familiarity with that platform is inevitably low at that time (as described in Scenario 1 and observed in Figure 35), because with few sales, limited opportunities exist for consumers to learn about the platform through word-of-mouth, such as observing those vehicles in use. With low consumer familiarity, the benefits of cost-reduction spillovers are greatly diminished, resulting in few incremental sales relative to Scenario 3.
Figure 35: 100% Spillovers of OEM Learning (Scenario 4)
4.6. Scenario 5: Spillovers of Consumer Word-of-Mouth

Having considered spillovers on the producer side of the market, I now consider the effect of spillovers of word-of-mouth on the consumer side of the market compared with Scenario 3, turning off cost-reduction spillovers considered in Scenario 4. Given that cost-reduction spillovers fail to influence the transition dynamics when consumer familiarity is low, the purpose of Scenario 5 is to explore whether spillovers of word-of-mouth between entrant platforms that accelerate the accumulation of consumer familiarity with the entrant platforms can help accelerate the transition from the hybrid technology to the radical technologies. In this scenario I assume that 100% of the socialization from word-of-mouth that consumers receive about entrant platform j spills over to the two other entrant platforms. For example, here I am assuming that if I speak with a friend about the PHEV they have purchased, I learn not only about the PHEV platform, but also about the related conventional hybrid HEV and fully electric BEV platforms equally, which share attributes of the PHEV platform. I assume that Familiarity spillovers do not occur to or from the conventional GAS platform, because consumers are already fully familiar with the GAS platform, and as a result social exposure to the GAS platform does not have novelty value that conveys new information about the entrant platforms. The simulation of this market is shown in Figure 36. In the presence of word-of-mouth spillovers, the entrant platforms are by definition exposed to more word-of-mouth that builds consumer familiarity with each platform. In relative terms, the breakdown of word-of-mouth by source below for the PHEV and BEV platforms can be seen to benefit the radical BEV platform most, which has the smallest installed base of vehicles and the fewest opportunities for consumer learning from direct word-of-mouth. Whereas the HEV platform receives 122% more word-of-mouth by year 2050 as a result of spillovers and the PHEV platform 131% more, the BEV platform receives 753% more word-of-mouth in the presence of spillovers. The effect of additional word-of-mouth is the faster accumulation of consumer familiarity, again most pronounced in the radical BEV platform, with consumers' average familiarity with the BEV platform 53% higher in the presence of word-of-mouth spillovers, compared with 10% and 14% for the HEV and PHEV platforms respectively. Now, a more rapid transition to the 100% electric BEV platform is observed, with the BEV achieving 17% of new vehicle sales by 2050, causing sales of the HEV and PHEV platforms to plateau by 2040. A 31% reduction in greenhouse gas emissions below 2000 levels is achieved by 2050 assuming EVs recharge with grid mix electricity, growing to a 43% reduction when renewable electricity is used, along with a 46% reduction in gasoline consumption. The results of Scenario 5 suggest that vehicle designs that maximize the potential for consumers to gather information that spills over to the PHEV and BEV platforms may be an important leverage
point to grow the EV market. For example, Toyota's growing family of Prius models (Figure A-5) are
distinctively styled, so as to be easily identified as unconventional, but share styling cues, helping
consumers to recognize similarities between the classic Prius hatchback and newer Prius models,
such as Prius HEVs with different body styles and the Prius Plug-In PHEV.
Figure 36: 100% Spillovers of Consumer Word-of-Mouth (Scenario 5)
4.7. Scenario 6: Marketing Spillovers

Car companies have long invested vast sums of money marketing new vehicles to consumers, from iconic Superbowl ads and newspaper inserts to Facebook campaigns, and recent EV launches have been no exception. Since the Chevrolet Volt PHEV and Nissan Leaf BEV were launched in late 2010, both companies have aggressively marketed their vehicles on television, particularly in response to criticism that sales of these vehicles had prematurely stagnated (Autoweek 2012; Fox News 2012). However, in doing so, much of Chevrolet’s advertising was a direct attack on the BEV platform, and Nissan’s advertising a direct attack on the PHEV platform, actively working against spillovers across platforms. Chevrolet’s ‘Anthem’ commercial for the Volt ends with the tag line “It’s More Car Than Electric”, evoking “....spontaneous acts of freedom”, an obvious criticism of the limited range of BEVs (Goodby Silverstein & Partners 2011). Nissan’s ‘What If Everything Ran on Gas?’ commercial for the Leaf shows a humorous world where everyday electrical appliances like toothbrushes and coffee makers are powered by noisy, smoke-spewing gasoline engines, even showing a Chevy Volt being refueled at the gas station (TWBA 2011), implying that vehicles using gasoline are inferior and emphasizing the conventional ICE/gasoline technology in the Volt rather than the fact that both the Volt and Leaf use an electric motor 100% of the time to send power to the drive wheels. Here I consider whether marketing that effectively highlighted the commonality between these entrant platforms could influence the transition dynamics. To do so, I assume that 100% marketing spillovers exist between entrant platforms, during the 10-year marketing program that occurs after a new platform is introduced and the assumed 0.5% of platform revenues spent on marketing after that time (turning off both cost-reduction and word-of-mouth spillovers). The simulation of this market is shown in Figure 37.
Figure 37: 100% Spillovers of Marketing (Scenario 6)

Vehicle Sales by Platform (vehicles/year)

Vehicle Installed Base by Platform (vehicles)

Annual GHGs (tonnes CO2-e/year)

Infr. Util. (dmnl) & Available Infr. (stations)

Consumer Familiarity with Platform (dmnl)

Platform Utility (dmnl)

PHEV Marketing Exposure ($/year)

BEV Marketing Exposure ($/year)
By definition, the spillovers of marketing increase the marketing exposure of each entrant platform, evidenced by the PHEV and BEV examples in Figure 37. With full marketing spillovers between entrant platforms, HEV marketing exposure is effectively 168% greater in year 2050 relative to a market with no spillovers (Scenario 3), PHEV marketing exposure is effectively 142% greater and BEV marketing exposure is effectively 369% greater. As in Scenario 5, marketing spillovers benefit the BEV platform the most in relative terms, which has the lowest sales and hence the least ability to invest in direct marketing. The effect of marketing spillovers is similar to the effect of word-of-mouth spillovers in Scenario 6: the additional socialization from marketing leads to consumers to accumulate familiarity with the entrant platforms more quickly, leading to faster adoption of these platforms and the beginnings of the transition away from the HEV and PHEV platforms to the 100% electric BEV platform, which has a sustaining market with 18% of new vehicle sales by 2050. The implication is similar to the case of word-of-mouth spillovers: marketing campaigns that educate consumers across multiple platforms, for example concentrating on innovative vehicle attributes that are shared across platforms, will contribute to the overall growth of the AFV market, but also help to accumulate resources (such as consumer familiarity, producer learning and refueling infrastructure) that can spill back to the target platform. Again, the marketing of the Prius family is instructive, as Toyota may have the strongest claim to having a portfolio of related vehicles across multiple technological platforms. Figure A-5 shows a Toyota ad in which the Prius family of HEV and PHEV vehicles are shown alongside each other, all colored white, inviting consumers to compare and contrast the features of these competing but related platforms. The ad emphasizes the growing choices available to consumers while emphasizing that even the new PHEV model is still a Prius, with all the experience, reliability, and other attributes consumers associate with the Toyota and Prius brands.

4.8. Scenario 7: Introduction of a Carbon Price

A key policy instrument to reduce GHG emissions is the introduction of a price on carbon emissions, through a carbon tax or emissions trading scheme. Here I implement a carbon price starting in year 2015, ramping up linearly over 10 years to the price of $150/tonne CO$_2$-e by year 2025 in a market with the following assumptions that are generally favorable to the radical EV platforms: 100% renewable electricity is used to recharge the PHEV and BEV platforms, so their operating costs are not affected by the carbon tax and 100% word-of-mouth spillovers are assumed that generate the transition dynamics described in Scenario 5. Further, I assume that the carbon intensity of the gasoline fuel stays constant (i.e. no low carbon biofuels or drop-in synthetic fuels...
are introduced) despite the strong economic incentive to do so given the price on carbon, and that the price of renewable electricity remains constant (i.e. no significant breakthroughs in renewable electricity generation costs occur), assuming no learning-by-doing or economies of scale exist in renewable electricity generation. The simulation of this market is shown in Figure 38. The effect of the carbon price can be clearly seen in the price of gasoline, which rises to over $5/gallon by year 2050, driving up the operating cost of the conventional GAS platform to more than 21 cents/mile by year 2050, while the operating cost of the BEV platform remains constant at 3.3 cents/mile, with the HEV and PHEV platforms in between. Rising operating costs have a negative impact on platform utility, causing the GAS platform to become steadily less attractive over time, leaving the PHEV as the highest utility platform by year 2030. The reinforcing consumer familiarity and infrastructure coevolution amplify these dynamics, reflected in the trajectory of new vehicle sales. Sales of the GAS platform fall to less than 5% market share by year 2050 as the carbon tax penalizes the carbon intensity of the conventional gasoline regime. The introduction of the carbon tax causes sales of the HEV and PHEV to grow strongly after 2020. However, as the price on carbon continues to grow, the HEV platform becomes less attractive also (given its dependence on gasoline) and the PHEV platform becomes the dominant technology, complemented by growing demand for the BEV platform, both characterized by high consumer familiarity, a sustaining market for recharging infrastructure and low operating costs. With these market assumptions, a 52% reduction in GHG emissions below 2000 is achieved by 2050, with the remaining emissions largely due to manufacturing and disposal of the vehicles, as opposed to their operating emissions. Scenario 7 highlights the impact a carbon price can have on the diffusion of these technologies, suggesting that a carbon price or other policies that raise gasoline operating costs (for example, raising the gasoline tax) are a high leverage point for interventions to accelerate the transition to EVs. The rising carbon price accelerates consumer adoption of the hybrid HEV platform initially, but also accelerates the transition away from the hybrid platform to the radical PHEV and BEV platforms, as word-of-mouth spills over across platforms and the HEV platform itself becomes expensive to operating with high gasoline and carbon prices.
Figure 38: Carbon Price + 100% Familiarity Spillovers + Renewable Electricity (Scenario 7)

Vehicle Sales by Platform (vehicles/year)

Vehicle Installed Base by Platform (vehicles)

Annual GHGs (tonnes CO2-e/year)

Infr. Util. (dmnl) & Available Infr. (stations)

Consumer Familiarity with Platform (dmnl)

Platform Utility (dmnl)

Gasoline Price ($/gallon)

Operating Cost (cents/mile)

[Image of graphs and charts showing various metrics like vehicle sales, installed base, annual GHGs, consumer familiarity, gasoline price, and platform utility over time for different scenarios.]
4.9. **Scenario 8: EV Infrastructure Availability**

While the above scenarios suggest new technology platforms will play an increasing role in the automotive market across a range of future market conditions, the prospect of a full and rapid transition across to EVs in the absence of some 'silver bullet' technological breakthrough remains uncertain. The perceived barriers to widespread adoption of EVs are numerous: PHEVs and BEVs are expensive, lack the ubiquitous refueling infrastructure available to gasoline vehicles, have a shorter (electric) range than gasoline vehicles, and recharging from L1/L2 rechargers takes hours. Here I focus on infrastructure-related barriers to EV adoption, considering how EVs might fare if recharging with electricity was every bit as convenient as refueling with gasoline is today. I assume that public EV recharging stations are all fast charging stations with identical attributes of gasoline refueling today, including the size of the installed base of stations and the speed with which refueling occurs. To operationalize Scenario 8, I assume an installed base of 120,000 fast recharging stations that all remain in the market regardless of their utilization, and I assume that recharging occurs at a power of 1MW, more than 100 times faster than the 7.2kW recharging power assumed in all earlier scenarios. In doing so, I ignore the numerous real-world barriers that make this rate of recharging infeasible at present. A 1MW recharging station would be dangerous to operate, would cause electricity grid instability when in use, would require highly advanced power electronics on-board the vehicle and would require an investment that would be likely to be uneconomic, in that the recharging revenues may not ever pay back the cost of installation. The simulation of this market is shown in Figure 39. With fast recharging, the BEV platform rapidly evolves to be the platform with the highest utility, as cost-reductions are achieved that reduce the purchase price of the vehicle. With the infrastructure coevolution feedback effectively turned off due to the assumption of ubiquitous fast recharging, and the time cost of refueling greatly reduced, the diffusion of the BEV platform is primarily governed by the consumer familiarity and producer learning feedback. Even so, this transition still plays out over multiple decades. Scenario 8 suggests that the availability of fast recharging infrastructure is a necessary but not sufficient condition for widespread consumer adoption of BEVs, otherwise BEVs would be expected to rapidly dominate new vehicle sales in this scenario. Even with an infrastructure comparable to the existing gasoline network, BEVs only comprise 40% of the light vehicle fleet by year 2050. Annual greenhouse gas emissions fall by 24% from year 2000 levels by 2050, and would fall by more than 50% if all BEVs refueled exclusively with renewable electricity.
5. Discussion

Given the success of HEVs in the United States over the past decade, when so many previous efforts to introduce AFVs have failed, it is timely to consider what role exists for HEVs when more radical PHEVs and BEVs that recharge directly from the electricity grid are now available to car buyers, and, to be specific, whether HEVs help or hinder the transition to these alternative fuel vehicles. Two alternative theories are presented here describing the role the HEVs could play in the EV market. The 'transitional technology' theory implies that HEVs have an important but temporary role to play in the automotive market, developing the technologies and consumer familiarity needed to successfully bring EVs to market. However, the success of HEVs at a time when significant barriers exist with all potential alternative fuels suggests that HEVs are not merely a stepping stone but a medium-term solution if energy and environmental policy goals are to be met. Analysis using the empirically grounded model of competing automotive platforms developed here suggests that in the absence of spillovers that facilitate the transition from the HEV to the PHEV and BEV platforms, competition from the HEV may stifle sales of the EV platforms, providing consumers with significant reductions in vehicle operating costs and greenhouse gas emissions at relatively low incremental purchase price. However, while the HEV can by definition never be a long-term solution to concerns and environmental pollution and energy security, and the HEV may impede a technological transition, the HEV may lead to biggest reductions in oil consumption and greenhouse gas emissions in the near-term, necessitating its deployment and creating a tension for policy-makers and the automotive industry.

Using the model to explore various market scenarios, I identify a number of opportunities for spillovers that could help to facilitate the transition from HEVs to PHEVs and BEVs. For automakers, the strategies used to style and market their advanced technology vehicles is a point of high leverage that will shape the relative success of the different entrant platforms. Product designs that are readily identified by consumers, such as the Kammback body style of the Toyota Prius, help consumers to become familiar with these new platforms most quickly. Conversely, vehicles that only differentiate advanced vehicles with an extra badge on the trunk, such as previous generations of the Honda Civic, Ford Escape and Toyota Camry, limit the potential to harness the reinforcing word-of-mouth feedback, because consumers may not even notice the advanced technology vehicle to learn that it has a hybrid or electric powertrain. Furthermore, styling cues that are shared across HEV and EV platforms, clearly signifying a new generation of automotive technology, will facilitate the spill over of consumer learning across platforms.
Similar opportunities exist in how these vehicles are marketed. Marketing campaigns that emphasize the positive and shared aspects of the various hybrid and electric vehicle platforms in the market will facilitate the spillover of marketing spending across these platforms, maximizing the effectiveness of marketing campaigns, particularly in light of potential flow-on effects from producer learning spillovers and the development of a ubiquitous electric vehicle recharging infrastructure. At present, the nature of the industry structure is such that firms have no incentive to market vehicles in a way that builds these spillovers, with firms aligned to individual platforms at present: Nissan’s Leaf BEV is competing with Chevrolet Volt 35-mile PHEV and Toyota’s Prius 15-mile PHEV. Only Toyota has any cohesive portfolio of technologies at present, with its Prius family of hybrid and plug-in hybrid variants. Until these companies each have a product portfolio that provides private incentives to market in a way that highlights the comprehensiveness of their product offerings, the cooperation of these firms may be required if marketing spillovers are to be realized. One way to achieve this could be for marketing to be undertaken through organizations such as the Alliance of Automobile Manufacturers. Another approach might be to tie government incentives for hybrid and electric vehicle adoption to informational campaigns that emphasize the similarities and differences of these advanced technology platforms.

For policy-makers, the scenario analysis informs how different policy designs may influence consumer adoption of hybrid and electric vehicles, and the subsequent impact on oil consumption and greenhouse gas emissions that may be achieved from the US light vehicle fleet. Compared with the diffusion rates needed to achieve future greenhouse gas emissions reduction targets, the rates of technology diffusion observed here are much slower. For example, the California Air Resources Board’s 2009 Zero Emissions Review includes a diffusion scenario that achieves an 80% reduction in California’s greenhouse gas emissions below 1990 levels by 2050 (Figure 11). It is important to note that CARB’s scenario is a ‘back-cast’, in which analysts determined the rates of adoption needed to achieve their target future emissions reduction, rather than simulate forward an explicit causal model as developed here. The CARB scenario reveals the mental model of the analysts, requiring aggressive consumer adoption of HEVs and PHEVs in the short to medium term, when then leave the market quickly to make way for 100% electric and hydrogen vehicles, with a smooth transition from HEV to PHEV to BEV. The scenario analysis undertaken here suggests the CARB dynamics are unlikely given the accumulation of consumer familiarity with new platforms and learning from production experience and R&D, even if the scenarios here are conservative parametrically. The rapid decline in sales of the HEV platform after 2020 may be explained by the absence of familiarity and learning feedbacks in the CARB model, ignoring the accumulated
consumer familiarity and production experience that has been gained if 40% of new vehicle buyers are choosing the HEV platform. Similarly, adoption of the radical BEV platform (and hydrogen fuel cell HFCV platform) at a rate faster than the HEV and PHEV platforms, which can refuel from the existing gasoline infrastructure and which share attributes with the conventional gasoline vehicle, suggests the CARB model lacks familiarity and infrastructure coevolution feedbacks, as the BEV and HFCV platforms each require the construction of their own ubiquitous refueling infrastructures to serve the installed base of vehicles. To accelerate this transition, my scenario analysis suggests that a carbon price is an effective policy instrument, if drivers of electric vehicles are recharging with renewable electricity (which itself will be incentivized by the carbon price), placing a wedge between the cost of gasoline miles and electric miles. However, it is important to recognize that the goals of emissions reduction and gasoline consumption in the short and long run are not perfectly aligned. Success in reducing emissions in the short term that is achieved through the adoption of conventional HEVs could make long-run emissions reduction harder than it might have been otherwise, if the successes of the hybrid HEV platform do not spillover to the radical EV platforms. While the turnover of the vehicle fleet may be well understood by policy-makers, the interaction with other feedbacks such as the accumulation of consumer familiarity, the realization of cost-reductions in key technologies and the co-evolution of infrastructure may be less well understood. Neglecting these feedbacks will lead analysts and policymakers to overstate the potential for change in energy use and emissions reduction from the adoption of new technologies. Careful
examination of the emerging market for plug-in electric vehicles in the United States, both temporally and spatially, will aid understanding both the existence and strength of these feedbacks.

6. Limitations and Future Opportunities

Numerous opportunities exist to further expand the boundary of the model, add additional disaggregate detail and address salient policy and strategy questions. The analysis here concentrates on the range of gasoline and electric vehicle technologies currently available in the United States, omitting other emerging vehicle and fuel technologies including ethanol and methanol flex-fuels, diesel, natural gas and hydrogen. Adding these platforms to the model will reveal interactions that exist between the electric powertrain pathway and other strategies such as the development of low-carbon liquid fuels that can be used in the conventional internal combustion engine. For the electric vehicle market, a major uncertainty in the environmental impact of electric vehicles is the carbon intensity of the electricity supply, treated here by considering the two extremes of a) the electricity grid as it stands today, and b) 100% use of electricity from renewable generation sources. Endogenous representation of the upstream fuel supply chain (for both electricity and other alternative fuel pathways) is a major opportunity to understand how demand from the automotive sector will influence the price and carbon intensity of these fuels over time, and, in turn, how the availability of those fuels influences consumer choices in the automotive market. Within the existing model, disaggregation from the technology level to the firm level, for both vehicles and recharging infrastructure, will add realism and the ability to analyze firm strategy decisions. At present, the model effectively represents each vehicle platform as an individual firm, when in reality each platform is being developed by multiple firms, and some firms such as Toyota are developing multiple platforms. The extent to which marketing and word-of-mouth spillovers are pursued by firms is likely to depend largely on their current portfolio of technological platforms. Considerable complexity also exists in the nascent EV recharging market, which currently isn't captured in the model. Whereas only 'slow' recharging is represented in the model currently, fast recharging and battery-switching technologies are also being developed that have the potential to benefit the 100% electric BEV platform in particular, and should be represented explicitly. Competing plug standards and competing payment systems within this market should also be represented, which have the potential to undermine the deployment of recharging infrastructure and consumer adoption of electric vehicles, if standards wars limit the extent to which electric vehicle drivers can access the existing infrastructure. Finally, the dynamic model developed can bring a new perspective to current strategy and policy debates, such as the
optimal PHEV battery capacity given impacts on battery learning, electricity use and vehicle purchase price (Shiau, Samaras et al. 2009), and the effect of Corporate Average Fuel Economy (CAFÉ) regulation on consumer adoption of AFVs.
References


Autoweek (2012). "GM stops Chevy Volt production to trim inventory."


Daily Mail (2012). The great Easter get nowhere: RAC warns that petrol panic buying risks millions of drivers not being able to fill their tanks for holiday break.


EIA (2012). "Table 5.6.B. Average Retail Price of Electricity to Ultimate Customers by End-Use Sector, by State, Year-to-Date through June 2012 and 2011."


Society of Automotive Engineers (2010). Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data.


The EV Project (2012). The EV Project FAQs.


Appendix A: Electric Vehicle Marketing Examples

Figure A-1: Chevrolet Volt "Anthem"

Figure A-2: Chevrolet Volt "Anthem"

It's More Car Than Electric.
Figure A-3: Nissan Leaf “What If Everything Ran On Gas?”

Figure A-4: Nissan Leaf “What If Everything Ran On Gas?”
Figure A-5: Toyota Prius “The Prius Family”

3rd gen prius
currently available

prius v
coming summer 2011

prius c concept
coming early 2012

prius plug-in hybrid (PHV)
available early 2012

*Prototype shown, actual production vehicle may vary.
Appendix B: Model Code

Fleet Turnover

Installed Base \(i\) [Technology] = New Vehicles \(i\) [Technology] + Used Vehicles \(i\) [Technology]
Units: vehicles

The installed base of vehicles by technology is the sum of New Vehicles and Used Vehicles.

New Vehicles \(i\) [Technology] = \(\text{INTEG} \) (Vehicle Sales \(i\) [Technology] - Vehicle Aging \(i\) [Technology] - New Vehicle Retirements \(i\) [Technology], "Initial Installed Base - New Vehicles \(i\) [Technology]"
Units: vehicles

The stock of New Vehicles accumulates new Vehicle Sales (indexed by technology \(i\)), and declines as vehicles age, becoming Used Vehicles, or are retired due to crashes and breakdowns.

Used Vehicles \(i\) [Technology] = \(\text{INTEG} \) (Vehicle Aging \(i\) [Technology] - Used Vehicle Retirements \(i\) [Technology], "Initial Installed Base - Used Vehicles \(i\) [Technology]"
Units: vehicles

The stock of Used Vehicles accumulates the aging of vehicles that were formerly New Vehicles, and declines as used vehicles are retired due to aging.

Vehicle Sales \(i\) [Technology] = Order Fulfillment \(j\) [Technology]
Units: vehicles/year

The rate of Vehicle Sales entering the fleet is given by the rate of order fulfillment occurring at dealerships, indexed by platform.

Vehicle Aging \(i\) [Technology] = New Vehicles \(i\) [Technology] / Aging Time Lambda
Units: vehicles/year

The rate of Vehicle Aging, indexed by technology, is formulated as the stock of New Vehicles by technology, divided by the assumed time for New Vehicles to age and become Used Vehicles.

New Vehicle Retirements \(i\) [Technology] = NV Discard Fr * New Vehicles \(i\) [Technology]
Units: vehicles/year

The rate of New Vehicle Retirements due to breakdowns and crashes, indexed by platform, is equal to the stock of New Vehicles multiplied by NV Discard Fr, the fraction of New Vehicles discarded each month.

Used Vehicle Retirements \(i\) [Technology] = Used Vehicles \(i\) [Technology] / Retirement Time
Units: vehicles/year

The rate of Used Vehicle Retirements, indexed by technology, is equal to the stock of Used Vehicles for each technology, divided by Retirement Time, the average lifetime that a vehicle survives as a Used Vehicle.

"Initial Installed Base - New Vehicles \(i\) [GAS] = 8e+07
"Initial Installed Base - New Vehicles \(i\) [HEV] = 0
"Initial Installed Base - New Vehicles \(i\) [PHEV40] = 0
"Initial Installed Base - New Vehicles \(i\) [BEV] = 0
"Initial Installed Base - Used Vehicles \(i\) [GAS] = 1.6e+08
"Initial Installed Base - Used Vehicles \(i\) [HEV] = 0
"Initial Installed Base - Used Vehicles \(i\) [PHEV40] = 0
"Initial Installed Base - Used Vehicles \(i\) [BEV] = 0
Units: vehicles

Initially, the installed base of all entrant platforms, both New and Used, is zero. Assuming a total installed base of light vehicles in the United States of 240 million vehicles, I assume that one third of these vehicles are New Vehicles, equal to 80 million, while the remaining two-thirds of these vehicles are Used Vehicles, equal to 160 million.
Discard Fr=0.01
Units: dmnl/year

The rate of New Vehicle Discards due to breakdowns and crashes is assumed to be 1% per year.

Aging Time Lambda=5
Units: year

The age at which New Vehicles age to become Used Vehicles, defined as Aging Time Lambda, is assumed to be 5 years.

Retirement Time=10
Units: year

The age of which Used Vehicles are retired on average assumed to be 10 years. Thus, the average lifetime of a vehicle in the model is 5 + 10 = 15 years.

Units: vehicles/year

The technology currently being driven by the buyer of a new vehicle influences their purchase decision. The number of New Vehicle Buyers who currently own a vehicle of platform i is the sum of the number of New Vehicle Retirements from platform i plus the number of Used Vehicle Retirements from platform i.

Familiarity

Cumulative Familiarity ij[Technology,TechnologyTo]= INTEG (Familiarity Discards ij[Technology,TechnologyTo]+Familiarity Increase ij[Technology,TechnologyTo]-Familiarity Forgetting ij[Technology,TechnologyTo]-Familiarity Sales ij[Technology,TechnologyTo],Initial Familiarity[Technology,TechnologyTo])
Units: vehicles

Familiarity is modeled using a co-flow structure to keep track of the effect of fleet turnover on consumer familiarity. The stock of Cumulative Familiarity the drivers of platform i have with platform j, measured in units of vehicles, accumulates with social exposure to platform j (Familiarity increase) and familiarity gained when a driver transfers from another platform (Familiarity Discards) and decreases with forgetting (Familiarity Forgetting) and the familiarity lost when a driver transfers to another platform (Familiarity Sales).

Familiarity Increase ij[Technology,TechnologyTo]=MAX(0,(1-Average Familiarity ij[Technology,TechnologyTo])*Total Social Exposure to Platform ij[Technology,TechnologyTo]*Installed Base ij[Technology])
Units: vehicles/year

Drivers of platform i gain familiarity with platform j through social exposure, assumed to occur at a diminishing rate as socialization saturation occurs. The Familiarity increase made by drivers of platform i as a result of social exposure to platform j (through marketing and word-of-mouth) is calculated as the Total Social Exposure that drivers of platform i get to platform j, multiplied by one minus the Average Familiarity those drivers have with platform j, the remaining Familiarity potential that exists in the gasoline driver population, multiplied by the number of platform i drivers in the fleet (Installed Base).

Average Familiarity ij[Technology,TechnologyTo]=IF THEN ELSE (TechnologyTo=GAS, 1, IF THEN ELSE (Technology=TechnologyTo, 1, ZIDZ(Cumulative Familiarity ij[Technology,TechnologyTo],Installed Base ij[Technology])))
Units: dmnl

The average familiarity that drivers of technology i have with technology j is calculated as the cumulative familiarity that drivers of technology i have with technology j (in units vehicles), divided by the number of drivers of technology i (also measured in vehicles). I assume that all platforms have full familiarity with the conventional GAS platform, given its ubiquity in the automotive market for more than 100 years.
Total Social Exposure to Platform $ij\{Technology,TechnologyTo\} = \text{Total Marketing Exposure } j\{TechnologyTo\} + \text{Cross Platform Exposure } ij\{Technology,TechnologyTo\}

Units: dmnl/year

Consistent with the Bass family of models, the total social exposure that drivers of technology $i$ receive with technology $j$ is the sum of social exposure from marketing (Total Marketing Exposure) plus social exposure from word-of-mouth (Cross Platform Exposure), both directly and as a result of spillovers.

Cross Platform Exposure $ij\{Technology,TechnologyTo\} = \begin{cases} \text{IF} & \text{THEN ELSE} \left[ \text{Time<Platform Introduction Date } j\{TechnologyTo\}, 0, \text{IF} \text{ THEN ELSE} \left[ \text{SW Word-of-Mouth Spillovers=0}, \text{Exposure from Driver } ij\{Technology,TechnologyTo\}, \text{SUM(Exposure from Drivers } ij\{Technology,TechnologySpill\} \ast \text{Word-of-Mouth Spillover Matrix } jk\{TechnologyTo,TechnologySpill\} \right] \right] \end{cases}

\text{Units: dmnl/year}

The extent of Cross Platform Exposure from word-of-mouth depends on the existence of word-of-mouth spillovers. If spillovers are inactive ($\text{SW Word-of-Mouth Spillovers}=0$), Cross Platform Exposure from word-of-mouth is equal to direct social Exposure from Drivers. If spillovers are active ($\text{SW Word-of-Mouth Spillovers}=1$), Cross Platform Exposure from word-of-mouth is sum of Exposure from Drivers multiplied by the Word-of-Mouth Spillover Matrix, summing over spillover platforms $k$.

Exposure from Drivers $ij\{TechnologyTo\} = \text{Effective Contact Rate Drivers} \ast \text{Probability of Contact with Drivers } j\{TechnologyTo\}

\text{Units: dmnl/year}

Inspired by the word-of-mouth formulation in the Bass model, the socialization effect of Exposure from Drivers of platform $j$ is the product of the rate at which effective contacts occur in the community, the Effective Contact Rate Drivers, and the likelihood that those contacts are with drivers of platform $j$, the Probability of Contact with Drivers. As in the Bass model, this formulation assumes that drivers of the different platforms are well mixed in the community.

Probability of Contact with Drivers $j\{TechnologyTo\} = \frac{\text{Installed Base } i\{TechnologyTo\}}{\text{SUM(Installed Base } i\{TechnologyTo\})}$

\text{Units: dmnl}

The Probability of Contact with a driver of platform $j$ is equal to the Installed Base of platform $j$, divided by the total Installed Base of vehicles of all platforms.

Effective Contact Rate Drivers $= 0.06$

\text{Units: dmnl/year}

The Effective Contact Rate with drivers of technology $k$ is the net rate at which contacts between potential adopters and adopters results in adoption of the Prius. This parameter represents the net effect of the contact rate and adoption rate parameters in the standard Bass model, assumed to be $0.06$.

Word-of-Mouth Spillover Matrix $jk\{TechnologyTo,TechnologySpill\} = \begin{cases} \text{IF} & \text{THEN ELSE} \left[ \text{TechnologyTo=} \text{TechnologySpill}, 1, \text{IF} \text{ THEN ELSE} \left[ \text{TechnologySpill=} \text{GAS}, 0, \text{Extent of Word-of-Mouth Spillovers} \right] \right] \end{cases}$

\text{Units: dmnl}

The Word-of-Mouth Spillover Matrix defines the extent to which social exposure to platform $k$ spills over to platform $j$. If platform $j$ equals platform $k$, the WoM Spillover Matrix takes the value 1, capturing the direct word-of-mouth effect from platform $j$. If platform $k$ is GAS, the WoM Spillover Matrix takes the value 0, because word-of-mouth is assumed to not spill over from the conventional GAS platform to any of the entrant platforms. In all other cases, the WoM Spillover Matrix takes the value given by the variable Extent of Word-of-Mouth Spillovers.

Extent of Word-of-Mouth Spillovers $= 0$

\text{Units: dmnl}

The extent of word-of-mouth spillovers is assumed to be 0 initially, and explored subsequently in Scenario 5.

Total Marketing Exposure $j\{TechnologyTo\} = \text{Marketing Effectiveness} \ast \text{SUM("Cross-Platform Marketing Spending } jk\{Technology,TechnologyTo\} \text{"})$

\text{Units: dmnl/year}
Consistent with the Bass family of models, the total marketing exposure to platform j that occurs is equal to the sum of cross-platform marketing exposure that is attributed to platform j, multiplied by the Marketing Effectiveness coefficient.

Units: million/year

The effective rate of marketing spending on platform j, taking marketing spillovers into account, is calculated as the extent of Marketing Spending on platform j, multiplied by the Marketing Spillover Matrix.

Marketing Spending j[TechnologyTo] = IF THEN ELSE( Platform Introduction Date j[TechnologyTo] < Time, IF THEN ELSE( Time < Marketing End Date j[TechnologyTo], Initial Spending by Platform j[TechnologyTo], Regular Marketing Spending j[TechnologyTo]), Regular Marketing Spending j[TechnologyTo])
Units: million/year

The amount spent marketing platform j depends on how long the platform has been in the market. For the duration of the initial marketing program, the amount of Marketing Spending is given by the variable Initial Spending by Platform. After that time, Marketing Spending is given by the variable Regular Marketing Spending.

Marketing End Date j[Technology] = IF THEN ELSE( Technology=GAS, 0, Platform Introduction Date j[Technology]+Marketing Duration)
Units: year

The Marketing End Date for platform j is calculated as the Platform Introduction Date for platform j plus the duration of the marketing program, in years.

Marketing Duration=10
Units: year

It is assumed that the initial marketing campaign lasts 10 years after a platform is first introduced.

Initial Spending by Platform j[TechnologyTo]=50
Units: million/year

It is assumed that the initial marketing campaign, for each platform j, involves spending 50 million/year on advertising.

Regular Marketing Spending j[Technology] = OEM Revenue j[Technology] / Dollars per Million * Marketing Fraction of Revenue
Units: million/year

Once the initial marketing campaign ends, it is assumed that marketing spending by platform reverts to a constant fraction of the revenue automotive manufacturers receive from sales of that platform.

OEM Revenue j[Technology] = Order Fulfillment j[Technology] * MSRP j[Technology]
Units: $/year

The revenue that automotive manufacturers receive from sales of technology j is calculated as the number of sales per year of technology j, multiplied by the manufacturers suggested retail price (MSRP) for those vehicles.

Marketing Fraction of Revenue=0.005
Units: dmnl

The fraction of platform revenue spent on marketing, after the expiration of the initial marketing program, is assumed to be 0.005 (0.5%).

Dollars per Million=1e+06
Units:$/million

Dollars per Million is equal to 1 million, used to convert from dollars to millions of dollars.
Marketing Spillover Matrix \( jk[\text{Technology}, \text{TechnologyTo}] = \begin{cases} 1, & \text{IF THEN ELSE} (\text{Technology} = \text{TechnologyTo}) \\ 0, & \text{IF THEN ELSE} (\text{Time} < \text{Platform Introduction Date} \[ \text{TechnologyTo} \], 0, \text{IF THEN ELSE} (\text{TechnologyTo} = \text{GAS}, 0, \text{IF THEN ELSE} (\text{TechnologyTo} = \text{GAS}, 0, \text{Extent of Marketing Spillovers}))) \end{cases} \)

Units: dmnl

The Marketing Spillover Matrix defines the extent to which marketing of platform \( k \) spills over to platform \( j \). If platform \( j \) equals platform \( k \), the WoM Spillover Matrix takes the value 1, capturing the direct effect of marketing platform \( j \). If platform \( k \) is GAS, the Marketing Spillover Matrix takes the value 0, because marketing is assumed to not spill over from the conventional GAS platform to any of the entrant platforms. In all other cases, the Marketing Spillover Matrix takes the value given by the variable Extend of Marketing Spillovers.

Extent of Marketing Spillovers = 0
Units: dmnl

The extent of marketing spillovers is assumed to be 0 initially, and explored subsequently in Scenario 6.

Marketing Effectiveness = 1.5e-05
Units: dmnl/million

The Marketing Effectiveness parameter is assumed to be 1.5e-05, implicitly assuming constant returns on marketing effort.

Familiarity Forgetting \( ij[\text{Technology}, \text{TechnologyTo}] = \begin{cases} \text{Effect of Social Exposure on Forgetting} \[ \text{ij} \[ \text{Technology}, \text{TechnologyTo} \] \times \text{Cumulative Familiarity} \[ \text{ij} \[ \text{Technology}, \text{TechnologyTo} \] \times \text{Normal Forget Rate Phi} \end{cases} \)

Units: vehicles/year

Drivers of technology \( i \) may forget about technology \( j \) if they do not receive regular social exposure to the new technology. The rate of Familiarity Loss is calculated as their current level of Familiarity, multiplied by the assumed Normal Forget Rate Phi, multiplied by the Effect of Social Exposure on Forgetting.

Normal Forget Rate Phi = 0.05
Units: dmnl/year

The rate at which drivers of technology \( i \) lost familiarity with technology \( j \) due to forgetting, the Normal Forget Rate Phi, is assumed to be 0.05 (5% per month).

Effect of Social Exposure on Forgetting \( ij[\text{Technology}, \text{TechnologyTo}] = \begin{cases} \text{MIN}(1, \text{MAX}(0, \text{Epsilon} * \text{Social Exposure Offset EtaRef} + 0.5 - \text{Epsilon} * \text{Total Social Exposure to Platform} \[ \text{ij} \[ \text{Technology}, \text{TechnologyTo} \])) \end{cases} \)

Units: dmnl

Here I suggest the Effect of Social Exposure on Forgetting is linear: consumers are likely to forget about platform \( j \) more quickly when their level of Familiarity with the Prius is low; conversely, their rate of forgetting is likely to be low when their level of Familiarity is high. Here the Effect of Social Exposure on Forgetting is formulated as a decreasing linear function with parameters Epsilon and Social Exposure Offset EtaRef.

Epsilon = 20
Units: dmnl/year

The forgetting parameter Epsilon is assumed to be 20.

Social Exposure Offset EtaRef = 0.05
Units: dmnl/year

The forgetting parameter Social Exposure Offset EtaRef is assumed to be 0.05.

Familiarity Discards \( ij[\text{Technology}, \text{TechnologyTo}] = \begin{cases} \text{SUM}(\text{Familiarity Swaps} \[ \text{ij} \[ \text{TechnologyFrom!}, \text{Technology}, \text{TechnologyTo} \]) \end{cases} \)

Units: vehicles/year

When a driver of platform \( i \) purchases a vehicle of platform \( j \), the population of drivers of platform \( j \) gain familiarity about the discarded platform. The familiarity gained from these discards is calculated by summing over technology \( I \) in the Familiarity Swaps matrix.
Familiarity Swaps $ij[TechnologyFrom,Technology,TechnologyTo] = \text{"Platform From/To if\"}[TechnologyFrom,Technology] \text{ IF THEN ELSE}[TechnologyTo = Technology, 1, Average Familiarity $ij[TechnologyFrom,TechnologyTo]]}$

Units: vehicles/year

The Familiarity Swaps matrix keeps track of the familiarity possessed by drivers swapping platforms. Drivers swapping from platform $i$ to platform $j$ take with them full familiarity about platform $i$, and Average Familiarity $ij$ about other platforms $k$.

"Platform From/To $ij[Technology,TechnologyTo] = \text{"Vehicle Discards } i\text{ New Vehicle Purchasers by Current Platform}\) $i[Technology]*Share ij[Technology,TechnologyTo]"$

Units: vehicles/year

The matrix Platform From/To is the number of drivers of platform $i$ who choose to purchase platform $j$. Platform From/To is calculated as the number of New Vehicle Purchasers by Current Platform, multiplied by the market share of technologies chosen by each of those driver populations.

Familiarity Sales $ij[Technology,TechnologyTo] = \text{Average Familiarity } ij[Technology,TechnologyTo]*"\text{Vehicle Discards } i\text{ New Vehicle Purchasers by Current Platform}\) $i[Technology]$}

Units: vehicles/year

When a driver who currently drives platform $i$ buys a platform $j$ vehicle, the stock of familiarity that the population of drivers of platform $i$ have with platform $j$ is reduced by the amount Average Familiarity $ij$. The total reduction in familiarity due to fleet turnover is equal to the number of New Vehicle Purchasers by Current Platform $i$, multiplied by their Average Familiarity $ij$.

**Vehicle Utility and Vehicle Market Share**

Share $ij[Technology,GAS] = \text{Liquid Fuel Share of Platform Nest } i[Technology]*ZIDZ(Affinity $ij[Technology,GAS]+Affinity $ij[Technology,HEV])$

Share $ij[Technology,HEV] = \text{Liquid Fuel Share of Platform Nest } i[Technology]*ZIDZ(Affinity $ij[Technology,GAS]+Affinity $ij[Technology,HEV])$

Share $ij[Technology,PHEV40] = (1-\text{Liquid Fuel Share of Platform Nest } i[Technology])*ZIDZ(Affinity $ij[Technology,PHEV40]+Affinity $ij[Technology,BEV])$

Share $ij[Technology,BEV] = (1-\text{Liquid Fuel Share of Platform Nest } i[Technology])*ZIDZ(Affinity $ij[Technology,PHEV40]+Affinity $ij[Technology,BEV])$

Units: dmnl

The market share of technology $j$ in new vehicle sales by drivers currently driving technology $j$ is calculated using a Nested Multinomial Logit (NMNL) discrete choice model. The share of technology $j$ is calculated as the share of technology $j$ within its nest (Liquid Fuel or Plug In) multiplied by the share of that nest compared with the other nest. The share of technology $j$ within its nest is calculated as the Affinity with technology $j$ by drivers of technology $i$, divided by the sum of the Affinities of the technologies in the nest.

Affinity $ij[Technology,TechnologyTo] = \text{Average Familiarity } ij[Technology,TechnologyTo]*\text{EXP Utility } ij[TechnologyTo]$

Units: dmnl

The Affinity that drivers of technology $i$ have with technology $j$ is equal to the average Familiarity drivers of technology $i$ have with technology $j$, multiplied by the exponential of the utility of technology $j$.

Liquid Fuel Share of Platform Nest $i[Technology] = \text{IF THEN ELSE}(\text{Inclusive Value Plug In Nest } i[Technology]=0, 1, \text{ IF THEN ELSE}(\text{Plug In Sector Active}=1, ZIDZ(\text{EXP}(\text{NMNL Lambda}*\text{Inclusive Value Liquid Fuel Nest } i[Technology]), (\text{EXP}(\text{NMNL Lambda}*\text{Inclusive Value Liquid Fuel Nest } i[Technology])+\text{EXP}(\text{NMNL Lambda}*\text{Inclusive Value Plug In Nest } i[Technology]))), 1))$

Units: dmnl

In the NMNL discrete choice model, the market share of each nest is calculated as the exponential of lambda multiplied by the inclusive value of that nest, divided by the sum of these exponential values for each nest. Here, with only two nests, calculation of the Liquid Fuel Nest also gives the share of the Plug In Nest $= 1 - \text{Liquid Fuel Nest}$. If plug-in vehicles have not yet entered the market, the market share of the Liquid Fuel Nest $= 1$. 193
NMNL Lambda=0.8
Units: dmnl

The lambda coefficient in the NMNL model is assumed to take the value 0.8.

Units: dmnl

The 'inclusive value' of the liquid fuel nest, capturing the representative utility of the vehicles in the liquid fuel nest, is calculated as the natural log of the sum of the affinities of the GAS and HEV platforms in the liquid fuel nest.

Inclusive Value Plug In Nest i[Technology]=IF THEN ELSE( (Affinity ij[Technology,PHEV40] + Affinity ij[Technology,BEV])>0, LN( Affinity ij[Technology,PHEV40] + Affinity ij[Technology,BEV]), 0)
Units: dmnl

The 'inclusive value' of the plug in nest, capturing the representative utility of the vehicles in the plug in nest, is calculated as the natural log of the sum of the affinities of the PHEV and BEV platforms in the plug in nest.

Plug In Sector Active= IF THEN ELSE(Platform Introduction Date j[PHEV40]<Time, 1, IF THEN ELSE(Platform Introduction Date j[BEV]<Time, 1, 0))
Units: dmnl

The variable Plug In Sector Active is a binary flag that takes the value 1 if one or both of the PHEV and BEV platforms has entered the market, taking the value 0 otherwise.

EXP Utility j[TechnologyTo]=IF THEN ELSE(Platform Introduction Date j[TechnologyTo]>Time, 0,EXP(Utility j[TechnologyTo/NMNL Lambda]))
Units: dmnl

EXP Utility is equal to the exponential of the utility of technology j, divided by the NMNL lambda coefficient. This intermediate step in the NMNL discrete choice calculation is calculated before the effect of Familiarity is incorporated, to ensure that the choice formulation is globally robust to negative utility values.

Utility j[TechnologyTo] = U1 j[TechnologyTo]+U2 j[TechnologyTo]+U3 j[TechnologyTo]+U4 j[TechnologyTo]+U5 j[TechnologyTo]+U6 j[TechnologyTo]+U7 j[TechnologyTo]
Units: dmnl

The Utility of technology j is the sum of the effect of the observable attributes of each technology: Purchase Price (U1), Operating Cost (U2), Acceleration (U3), Top Speed (U4), Greenhouse Gas Emissions (U5), Refueling Cost (U6) and Product Scope (U7).

U1 j[TechnologyTo]=((Effective Price j[TechnologyTo])/1000)/"Ln(Household Income)"**Purchase Price Weight
Units: dmnl

The effect of the purchase price of technology j on utility, U1, is formulated as a function of both the effective purchase price of the technology and the household income of the consumer. Specifically, U1 is estimated as the Effective Price of technology j (in thousands of dollars), divided by the natural log of Household Income (in thousands of dollars), multiplied by the Purchase Price Weight. Taking the natural log of Household Income captures the concept that consumers become less sensitive to price as their income increases.

Purchase Price Weight=-0.361
Units: dmnl/($/vehicles)

Purchase Price Weight is assumed to be -0.361 (Brownstone, Bunch et al. 2000).

Effective Price j[TechnologyTo]=MSRP j[TechnologyTo]-Vehicle Incentives j[TechnologyTo]+EV Home Charger Cost j[TechnologyTo]
Units: $/vehicles
The effective price of technology $j$ is calculated as the Manufacturer's Suggested Retail Price (MSRP), less any incentives offered to encourage adoption of that technology, plus the cost of a home recharging point if the technology is a plug-in vehicle (PHEV or BEV). Implicitly, it is assumed that consumers only buy a plug-in electric vehicle if they can recharge it at home.

\[
\text{MSRP}_j(\text{Technology}) = (1 + \text{Markup}) \times (\text{Base Vehicle Cost}_i(\text{Technology}) + \text{IC Engine Cost}_i(\text{Technology}) + \text{Electric Architecture Cost}_i(\text{Technology}) + \text{Battery Cost}_i(\text{Technology}))
\]

Units: $/vehicles

The manufacturing cost of technology $k$ is calculated as the sum of the manufacturing costs of the platform’s components (base vehicle, internal combustion, electric power architecture and traction battery, as implemented differentially by each platform). The Manufacturer’s Suggested Retail Price for technology $j$ is assumed to be calculated using a simple cost-markup heuristic, calculated by multiplying the manufacturing cost by one plus the markup fraction.

\[
\text{Markup} = 0.1
\]

Units: dmnl

The pricing markup applied over the platform manufacturing cost is assumed to be 10%.

\[
\text{Vehicle Incentives}_j(\text{TechnologyTo}) = \text{Incentive Value}_j(\text{TechnologyTo}) \times \text{Incentive Active}_j(\text{TechnologyTo})
\]

Units: $/vehicles

The value of vehicle incentives being offered for technology $j$ is calculated as the value of incentives for technology $j$ multiplied by the Incentive Active flag, which indicates whether the incentive is currently available for technology $j$.

\[
\text{Incentive Value}_j(\text{TechnologyTo}) = \min(\text{Incentive Cap}, \text{Battery}_i(\text{TechnologyTo}) \times "$/kWh Incentive")
\]

Units: $/vehicles

The value of the incentive offered for the purchase of technology $j$ is calculated as the size of technology $j$’s battery (in kilowatt-hours), multiplied by the incentive offered per kilowatt-hour of traction battery, capped at the maximum level given by the variable Incentive Cap.

\[
"$/kWh Incentive" = 250
\]

Units: $/(kW*hour)

The incentive offered per kilowatt-hour of traction battery is assumed to be $250, the amount currently being offered by the US federal government’s electric vehicle incentive.

\[
\text{Incentive Cap} = 7500
\]

Units: $/vehicles

The maximum incentive available to consumers for the purchase of a plug-in electric vehicle is assumed to be $7,500, consistent with the incentive currently being offered by the US federal government.

\[
\text{Incentive Active}_j(\text{Technology}) = \text{IF THEN ELSE}(\text{Time}<\text{Platform Introduction Date}_j(\text{Technology}), 1, 0)
\]

Units: dmnl

Incentives are offered immediately after a platform is first introduced, for a number of years given by the variable Incentive Duration. Incentive Active is a binary flag, indexed by technology, which takes the value 1 if incentives are currently available for technology $j$, and 0 otherwise.

\[
\text{Platform Introduction Date}_j(\text{GAS}) = 1900
\]
\[
\text{Platform Introduction Date}_j(\text{HEV}) = 2000
\]
\[
\text{Platform Introduction Date}_j(\text{PHEV40}) = 2010
\]
\[
\text{Platform Introduction Date}_j(\text{BEV}) = 2010
\]

Units: year

Historically, the first gasoline vehicles were available to US car buyers in 1900, the early Honda Insight and Toyota Prius HEVs were available from 2000, and the PHEV and BEV platforms were introduced in 2010 with the availability of the Chevrolet Volt and Nissan Leaf vehicles respectively.
Incentive Duration = 10
Units: year

It is assumed that incentives are offered for a duration of 10 years.

EV Home Charger Cost \( j[\text{Technology}] \) = 0, 0, 2000, 2000
Units: $/vehicles

The price of a home recharging unit is assumed to be $2,000. This cost is incurred by buyers of the PHEV and BEV platforms which can recharge directly from the electric grid, but not the GAS and HEV platforms that refuel using gasoline exclusively.

\[ U_2[j[\text{TechnologyTo}]] = \text{Operating Cost Weight} \times \text{Operating Cost } j[\text{TechnologyTo}] \]
Units: dmnl

The effect of operating on utility of technology \( j \), \( U_2 \), is equal to the operating cost of technology \( j \) in cents per mile, multiplied by the weight placed on this attribute, Operating Cost Weight.

\[ \text{Operating Cost } j[\text{TechnologyTo}] = \left[ (1 - \% \text{ All Electric Miles by Platform } j[\text{TechnologyTo}]) \times \text{Gasoline Operating Cost } j[\text{TechnologyTo}] \right] + \left[ \% \text{ All Electric Miles by Platform } j[\text{TechnologyTo}] \times \text{Electric Operating Cost } j[\text{TechnologyTo}] \right] \]
Units: cents/miles

The Operating Cost of technology \( j \) (cents/mile) is calculated as the weighted average of technology \( j \)'s operating cost using gasoline and technology \( j \)'s operating cost using electricity, weighted by the fraction of miles driven using each fuel.

\[ \text{Gasoline Operating Cost } j[\text{Technology}] = \frac{ZIDZ(\text{Effective Gas Price, FE by Platform } i[\text{Technology}])}{\text{ FE by Platform } i[\text{Technology}]} \]
Units: cents/miles

The operating cost of technology \( j \) using gasoline (cents/mile) is equal to the price of gasoline in cents per gallon, Effective Gas Price, divided by the fuel economy of technology \( j \) in miles per gallon.

\[ \text{Electric Operating Cost } j[\text{Technology}] = \text{Effective Electricity Price} \times \text{EE by Platform } i[\text{Technology}] \]
Units: cents/miles

The operating cost of technology \( j \) using electricity (cents/mile) is equal to the price of electricity in cents per kilowatt-hour, Effective Electricity Price, multiplied by the energy efficiency of technology \( j \) in kilowatt-hours per mile.

\[ \text{Operating Cost Weight} = -0.17 \]
Units: dmnl/(cents/miles)

Operating Cost Weight is assumed to be -0.17 (Brownstone, Bunch et al. 2000).

\[ U_3[j[\text{TechnologyTo}]] = \text{Acceleration Weight} \times \text{UPL Acceleration } j[\text{TechnologyTo}] \]
Units: dmnl

The effect of vehicle acceleration on utility of technology \( j \), \( U_3 \), is equal to the 0-30 acceleration of technology \( j \) in seconds, multiplied by the weight placed on this attribute, Acceleration Weight.

\[ \text{Acceleration Weight} = -0.149 \]
Units: dmnl/seconds

Acceleration Weight is assumed to be -0.149 (Brownstone, Bunch et al. 2000).

\[ U_4[j[\text{TechnologyTo}]] = \text{Top Speed Weight} \times \text{Top Speed by Platform } j[\text{TechnologyTo}] \]
Units: dmnl

The effect of vehicle performance on the utility of technology \( j \), \( U_5 \), is equal to the Top Speed Weight multiplied by the top speed of platform \( j \), measured in miles per hour.

\[ \text{Top Speed Weight} = 0.272 \]
Units: dmnl
Top Speed Weight is assumed to be 0.272 (Brownstone, Bunch et al. 2000).

\[ U_5[\text{TechnologyTo}] = \text{Emissions Fr Weight} \times \text{Emissions Fraction}_j[\text{TechnologyTo}] \]
Units: dmnl

The effect of greenhouse gas emissions on the utility of technology \( j \), \( U_5 \), is equal to the Emissions Fraction Weight multiplied by the greenhouse gas emissions by technology, measured as annual greenhouse gas emissions as a fraction of the annual greenhouse gas emissions of an equivalent gasoline vehicle.

Emissions Fr Weight= 0.149
Units: dmnl

Emissions Fr Weight is assumed to be -0.149. This assumption is the average of the Stated and Revealed preference coefficient estimates from Brownstone, Bunch et al. (2000).

\[ U_6[\text{TechnologyTo}] = \text{Refueling Cost}_j[\text{TechnologyTo}] \times \text{Operating Cost Weight} \]
Units: dmnl

The cost of refueling (station search, queue time, service time and out-of-fuel risk) is calculated as an incremental operating cost, measured in cents/mile calculated on an annual basis. The effect of refueling cost on the utility of technology \( j \), \( U_6 \), is equal to the refueling cost in cents/mile, multiplied by the Operating Cost Weight.

\[ \text{Refueling Cost}_j[\text{TechnologyTo}] = \text{Annual Refueling Cost}_i[\text{TechnologyTo}] \times \frac{\text{Cents per Dollar}}{\text{VMT per Year}_i[\text{TechnologyTo}]} \]
Units: cents/miles

The refueling cost of platform \( j \), in cents per mile, is calculated as the Annual Refueling Cost, in dollars/year, multiplied by Cents per Dollar to convert the Annual Refueling Cost to cents/year, divided by the number of vehicle miles traveled each year, VMT per Year.

VMT per Year \( i[\text{Technology}] = 12000 \)
Units: miles/vehicles/year

The assumed number of vehicle miles traveled per year is assumed to be 12,000, consistent across all platforms.

\[ U_7[\text{Technology}] = \frac{-\text{Scope Weight}}{1 + \exp\left(-\text{Sensitivity} \times \text{Delivery Fraction of Scope Threshold}_j[\text{Technology}] + \text{Sensitivity}/2\right)} + \text{Scope Weight} \]
Units: dmnl

The effect of scope of utility is assumed to be a logistically increasing function (with parameters Scope Weight and Sensitivity) of the fraction of the vehicles of the scope threshold, which indicates when platform \( j \) has reached sufficient cumulative sales to be offering a full scope of body styles.

\[ \text{Delivery Fraction of Scope Threshold}_j[\text{Technology}] = \text{ZIDZ}(\text{Cumulative Order Fulfillment}_j[\text{Technology}], \text{Reference Deliveries}) \]
Units: dmnl

The Delivery Fraction of Scope Threshold is calculated as the cumulative number of sales of platform \( j \), divided by the reference number of deliveries that indicate a full product scope for platform \( j \).

\[ \text{Cumulative Order Fulfillment}_j[\text{Technology}] = \text{INTEG} \left( \text{Order Fulfillment}_j[\text{Technology}], 0 \right) \]
Units: vehicles

Cumulative sales (order fulfillment) is the accumulation of annual sales (order fulfillment) of platform \( j \), taking the value 0 initially.

Reference Deliveries = 2e+07
Units: vehicles

The reference number of deliveries for the product scope threshold is assumed to be 20 million vehicles.
Sensitivity=10
Units: dmnl

The Sensitivity parameter for scope is assumed to take the value 10.

Scope Weight=-0.5
Units: dmnl

The Scope Weight coefficient is assumed to take the value -0.5.

**Refueling Cost**

Annual Refueling Cost if[Technology,Infrastructure]=SUM(Annual Refueling Cost if[Technology,Infrastructure])
Units: $/year/vehicles

The annual refueling cost of platform i is the sum of the annual cost of refueling platform i across each of the infrastructures f used by platform i.

Units: $/year/vehicles

The annual refueling cost of platform i using infrastructure f is the sum of the costs associated with refueling a vehicle: the time cost of searching for refueling stations, the time cost of queuing to access the refueling station, the time cost of refueling and the time cost of the risk that the driver runs out of fuel before a refueling station is found.

Annual Search Cost if[Technology,Infrastructure]=Refuels per Year if[Technology,Infrastructure]*Average Refueling Distance if[Infrastructure]*(Value of Time/Average Speed)
Units: $/year/vehicles

The annual search cost for a driver of platform j using fuel f is calculated as the number of Refuels per Year made, multiplied by the Average Refueling Distance to a station of infrastructure f, multiplied by the cost per mile driving, calculated as the Value of Time divided by Average Speed.

Value of Time=40
Units: $/hour

Consumers' value of time is assumed to be $40/hour.

Average Speed=40
Units: miles/hour

The average driving speed of all platforms is assumed to be 40 miles/hour.

Refuels per Year if[Technology,Infrastructure]=ZIDZ(VMT by Fuel by Platform if[Technology,Infrastructure],Effective Range if[Technology,Infrastructure])
Units: dmnl/year

The number of Refuels per Year made by drivers of platform i using infrastructure f is calculated as the number of vehicle miles traveled by drivers of platform i using infrastructure f divided by the Effective Range of platform i using infrastructure f.

Effective Range if[Technology,Infrastructure]=MAX(Nomina Range if[Technology,Infrastructure]-Optimal Buffer No PHEV Battery Buffer if[Technology,Infrastructure],0)
Units: miles/vehicles

The effective range of platform j using fuel f is the nominal range of platform j using fuel f less the optimal buffer that minimizes the annual cost of refueling platform j using fuel f.
Optimal Buffer

For the PHEV platform, the Optimal Buffer is zero, because the backup gasoline engine is available when the PHEV traction battery is depleted.

The optimal buffer for platform i is given by the variable Gasoline Buffer for the GAS, HEV and PHEV platforms, and the variable BEV Electricity Buffer for the BEV platform. The electricity buffer only applies to the BEV platform, because I assumed previously that the PHEV platform does not require an electricity buffer.

The annual refueling cost with respect to the buffer is a U-shaped function, as search costs, queuing costs and service costs increase with larger buffers, while the out-of-fuel risk is reduced. The optimal gasoline buffer for platform i minimizes the annual gasoline refueling cost, found at the point where the derivative of annual gasoline refueling cost equals zero.

The annual refueling cost with respect to the buffer is a U-shaped function, as search costs, queuing costs and service costs increase with larger buffers, while the out-of-fuel risk is reduced. The optimal electric buffer for the BEV platform minimizes the annual electricity refueling cost, found at the point where the derivative of annual electricity refueling cost equals zero.

The annual vehicle miles traveled by platform i is calculated as the annual vehicle miles traveled by platform i, multiplied by the Vehicle to Station Map that defines the share of miles traveled using each fuel.

The Vehicle to Station Map defines the dependence of vehicle platform i on infrastructure f. For plug-in electric vehicles, the dependence on public recharging infrastructure depends on the size of the vehicle battery, which influences the percentage of VMT fueled by nightly private recharging at home.

The percentage of annual VMT driven using gasoline, by platform i, is equal to one minus the percentage of annual VMT driven using electricity.
The percentage of electric miles driven by drivers of platform i is the sum of the percentage of public electric miles driven per platform (i.e. electric miles for which recharging occurred at public infrastructure) and the percentage of private electric miles driven per platform (i.e. electric miles for which recharging occurred at private infrastructure).

"% Private Electric Miles by Installed Base Platform i[Technology]= IF THEN ELSE(Technology=PH40, "TF % Electric Miles CDF(Nominal Range if[Technology,PLUG]**Units Correction Miles/Vehicles"), IF THEN ELSE(Technology=BEV, "TF % Electric Miles CDF(Effective Range if[Technology,PLUG]**Units Correction Miles/Vehicles"))

The formulation for the percentage of private electric miles differs by platform. For the all-electric BEV platform, the % electric miles fueled by home recharging is a function of the Effective Range of the platform, as the fuel buffer is needed in order to find a recharging station if daily miles exceed the BEV range. For the PHEV platform, no buffer is needed, because the gasoline engine is available if daily miles exceed the PHEV range.

"TF % Electric Miles CDF([0,0]-[180,1],[0,0],[20,0.046],[40,0.091],[60,0.136],[80,0.18],[100,0.222],[120,0.264],[140,0.304],[160,0.342],[180,0.379],[200,0.415],[220,0.449],[240,0.482],[260,0.513],[280,0.542],[300,0.57],[320,0.597],[340,0.622],[360,0.646],[380,0.669],[400,0.69],[420,0.71],[440,0.73],[460,0.747],[480,0.764],[500,0.78],[520,0.795],[540,0.809],[560,0.822],[580,0.835],[600,0.846],[620,0.857],[640,0.867],[660,0.877],[680,0.886],[700,0.894],[720,0.902],[740,0.909],[760,0.916],[780,0.922],[800,0.928],[820,0.933],[840,0.938],[860,0.943],[880,0.948],[900,0.952],[920,0.956],[940,0.959],[960,0.962],[980,0.966],[1000,0.968],[1020,0.971],[1040,0.973],[1060,0.976],[1080,0.978],[1100,0.98],[1120,0.982],[1140,0.983],[1160,0.985],[1180,0.986],[1200,0.987],[1220,0.989],[1240,0.99],[1260,0.991],[1280,0.992],[1300,0.993],[1320,0.994],[1340,0.994],[1360,0.994],[1380,0.995],[1400,0.996],[1420,0.9965],[1440,0.997],[1460,0.9973],[1480,0.9977],[1500,1])

This table function TF % Electric Miles CDF defines the assumed % of electric miles driven by a PHEV for a given all-electric range.

"% Public Electric Miles by Installed Base Platform i[Technology]= IF THEN ELSE(Technology=BEV, 1-"% Private Electric Miles by Installed Base Platform i[BEV], IF THEN ELSE(Technology=PH40, (1-"% Private Electric Miles by Installed Base Platform i[PH40])(1-"% PHEV Public Miles Gasoline v Electric i[PH40])0))

For the BEV platform, the % electric miles from public recharging infrastructure is equal to one minus the % electric miles from private recharging. For the PHEV platform, the % electric miles from public recharging infrastructure is the balance of miles not fueled by private recharging or from gasoline.

"% PHEV Public Miles Gasoline v Electric i[Technology]= EXP(Refueling Utility if[Technology,GASPUMP])/(EXP(Refueling Utility if[Technology,GASPUMP]) +EXP(Refueling Utility if[Technology,PLUG]))

When a PHEV driver has depleted their traction battery, they have a choice of recharging using public recharging infrastructure, or driving using gasoline, which is effectively a choice to refuel using gasoline. This decision is modeled as a binary logit choice, where the % PHEV public miles using gasoline is given by the exponential of the Refueling Utility using gasoline, divided by the sum of the exponentials of Refueling Utility for both gasoline and electricity.

Refueling Utility if[Technology,Infrastructure]=R1 if[Technology,Infrastructure]+R2 if[Infrastructure]

The utility of refueling from infrastructure f for PHEVs is the sum of the effect of refueling time (R1) and refueling distance (R2) on utility.

R1 if[Technology,Infrastructure]=Refueling Time Weight*Refueling Time if[Technology,Infrastructure]

The effect of Refueling Time on utility for drivers of platform i using infrastructure f is calculated as the Refueling Time multiplied by the Refueling Time Weight.

R2 f[Infrastructure]=Refueling Distance Weight*Average Refueling Distance f[Infrastructure]
Units: $/year/vehicles

The Out-of-Fuel Risk for the PHEV platform using electricity is assumed to be zero, because the backup gasoline engine is available when the PHEV traction battery is depleted.
Units: $/year/vehicles

The Annual Out-of-Fuel Risk Cost for platform i using infrastructure f is calculated as the number of Refuels per Year, multiplied by the probability of running out-of-fuel at each refueling event, multiplied by the time required to recover from running out-of-fuel, multiplied by the value of that time.

"Out-of-Fuel Recovery Time" = 2
Units: hour/vehicles

The time required to recover following an out-of-fuel event is assumed to be 2 hours.

"P(Out-of-Fuel) if [Technology, Infrastructure] = 1/(1 + (ZIDZ(0, Optimal Buffer if [Technology, Infrastructure], Average Distance to Station if [Infrastructure]) ^ "Out-of-Fuel Beta"))
Units: dmnl

The probability of running out-of-fuel decreases as the fuel buffer increases, because the driver has a larger operating range with which to find a refueling station. This non-linear effect is modeled using a negative exponential function which takes the value 1 when the fuel buffer is 0, and declines as the fuel buffer increases.

"Out-of-Fuel Beta" = 3
Units: dmnl

The Out-of-Fuel Beta sensitivity parameter in the Out-of-Fuel probability formulation is assumed to equal 3.

Average Distance to Station if [Infrastructure] = SQRT(ZIDZ(US Area Square Miles, Available Infrastructure if [Infrastructure]))
Units: miles

The Average Distance to a refueling Station of infrastructure f is given by the square root of the average number of square miles per station, assuming spatial Poisson placement of infrastructure (i.e. no strategic infrastructure placement).

Units: $/year/vehicles

The Annual Time Cost of Refueling for platform i using infrastructure f is the sum of the time cost of public refueling plus the time cost of private refueling. Time spent refueling at public infrastructure is calculated as the Refueling Time per refueling event, multiplied by the number of Refuels per Year. Time spent refueling at private infrastructure is assumed to only be the time required to plug the vehicle in to the recharging point, estimated as the number of Home Recharges per Year multiplied by the Time Cost of Home Recharging.

Home Recharges per Year if [Technology] = 0, 0, 200, 200
Units: 1/year

The number of home recharges per year by drivers of the plug-in PHEV and BEV platforms is assumed to be 200, and 0 for the gasoline fueled GAS and HEV platforms.

Time Cost of Home Recharging = 1/60
Units: hour

The time cost of home recharging is assumed to be 1/60th of an hour (1 minute).

Annual Queuing Cost if [Technology, PLUG] = Electricity Queueing Cost * Refuels per Year if [Technology, PLUG]
Units: $/year/vehicles
The annual time cost of queuing for infrastructure $f$ is calculated as the queuing cost per refueling event per vehicle platform, multiplied by the number of Refuels per Year made by platform $i$ at infrastructure $f$.

Gasoline Queueing Cost $i[Technology]=$Value of Time*Target Queue Time $f[GASPUMP]*[(1/((1-Infrastructure Utilization $f[GASPUMP])^Alpha))]/(Target Utilization $f[GASPUMP]/(1-Target Utilization f[GASPUMP]))$
Units: $/vehicles

The time cost of queuing for infrastructure grows non-linearly as infrastructure utilization increases. Here, the gasoline infrastructure queuing time is estimated as a hyperbolic function, multiplied by the Value of Time to convert to a queuing cost.

Electricity Queueing Cost=$Value of Time*Target Queue Time f[PLUG]*[(1/((1-Infrastructure Utilization $f[PLUG])^Alpha))]/(Target Utilization f[PLUG]/(1-Target Utilization $f[PLUG]))$
Units: $/vehicles

The time cost of queuing for infrastructure grows non-linearly as infrastructure utilization increases. Here, the electricity infrastructure queuing time is estimated as a hyperbolic function, multiplied by the Value of Time to convert to a queuing cost.

Target Queue Time $f[Infrastructure]=0.08$
Units: hour/vehicles

The target queuing time for infrastructure $f$ is assumed to be 0.08 hours (5 minutes).

Alpha=1
Units: dmnl

The Alpha sensitivity parameter in the Queueing Cost formulation is assumed to equal 1.

**Infrastructure Coevolution**

Available Infrastructure $f[Infrastructure]$= INTEG (Exogenous Infrastructure $f[Infrastructure]$+Infrastructure Construction $f[Infrastructure]$-Infrastructure Exits $f[Infrastructure]$).Initial Infrastructure Availability $f[Infrastructure]$)
Units: stations

The stock of Available Infrastructure for infrastructure $f$ accumulates Exogenous infrastructure installation and endogenous Infrastructure Construction, and declines with Infrastructure Exits. Initially, 120,000 gasoline stations exist in the United States, representative of today's gasoline station network, while it is assumed that 5,000 recharging points exist.

Infrastructure Construction $f[Infrastructure]$=IF THEN ELSE([Desired Change in Infrastructure $f[Infrastructure]$]>0, ZIDZ([Desired Change in Infrastructure $f[Infrastructure]$], Time to Install Infrastructure $f[Infrastructure]$), 0)
Units: stations/year

If the Desired Change in Infrastructure is greater than zero (i.e. more infrastructure is desired), the Infrastructure Construction rate for infrastructure $f$ is given by the Desired Change in Infrastructure, divided by the Time to Install Infrastructure $f$.

Time to Install Infrastructure $f[Infrastructure]=1,0.5$
Units: year

The time needed to plan and install new refueling stations is assumed to be 1 year for gasoline pumps, and 0.5 years for recharging points.

Desired Change in Infrastructure $f[Infrastructure]=Available Infrastructure $f[Infrastructure]$*Utilization Gap $f[Infrastructure]$
Units: stations

The Desired Change in Infrastructure (stations) for infrastructure $f$ is calculated as the Available Infrastructure (stations) multiplied by the Utilization Gap for that infrastructure (dimensionless).
Exogenous Infrastructure $f[GSPUMP] = 0$
Exogenous Infrastructure $f[PLUG] = \text{Stations per Year} \times \text{Pulse(PHEV40 Introduction Date - 0.5, Program Duration)} \times \text{Pulse(BEV Introduction Date - 0.5, Program Duration)}$
Units: stations/year

I assume that a recharging infrastructure development program is undertaken for the time period Program Duration, starting 0.5 years before each plug-in platform is introduced. For each platform for each year of the program, the number of stations installed is given by the variable Stations per Year. No exogenous infrastructure is undertaken for the conventional gasoline infrastructure, which is already ubiquitous and financially viable.

Program Duration = 10
Units: year

The recharging infrastructure development program that occurs after either of the plug-in EV platforms are introduced is assumed to run for 10 years.

Stations per Year = 5000
Units: stations/year

During the recharging infrastructure development program, it is assumed that 5,000 recharging points are installed per year.

Infrastructure Exits $f[\text{Infrastructure}] = \text{MAX}((\text{Available Infrastructure} f[\text{Infrastructure}] / \text{Infrastructure Life} f[\text{Infrastructure}]) , \text{Removal Rate due to Utilization} f[\text{Infrastructure}])$
Units: stations/year

The rate of Infrastructure Exits for infrastructure $f$ is the greater of the regular rate of infrastructure retirements, given by Available Infrastructure $f$ divided by the Infrastructure Life in year, and the Removal Rate due to Utilization, if the Desired Change in Infrastructure is less than zero.

Infrastructure Life $f[\text{Infrastructure}] = 20$
Units: year

The average lifetime of infrastructure $f$ is assumed to be 20 years.

Removal Rate due to Utilization $f[\text{Infrastructure}] = \text{IF THEN ELSE}(\text{Desired Change in Infrastructure} f[\text{Infrastructure}] < 0, \text{ZIDZ}(\text{Desired Change in Infrastructure} f[\text{Infrastructure}], \text{Time to Remove Infrastructure} f[\text{Infrastructure}]), 0)$
Units: stations/year

If the Desired Change in Infrastructure for infrastructure $f$ is less than zero (i.e. the current infrastructure is under-utilized), the Removal Rate due to Utilization is given by the Desired Change in Infrastructure divided by the Time to Remove Infrastructure. If the Desired Change in Infrastructure is greater than or equal to zero, the Removal Rate due to Utilization is zero.

Time to Remove Infrastructure $f[\text{Infrastructure}] = 1$
Units: year

The time to plan and implement the removal of a station of infrastructure $f$ is assumed to be 1 year.

Utilization Gap $f[\text{Infrastructure}] = \text{Projected Infrastructure Utilization} f[\text{Infrastructure}] - \text{Target Utilization} f[\text{Infrastructure}]$
Units: dmnl

The Utilization Gap for infrastructure $f$ is the difference between the Projected level of Infrastructure Utilization and the Target level of Infrastructure Utilization.

Target Utilization $f[\text{Infrastructure}] = 0.2$
Units: dmnl

The Target Utilization fraction for infrastructure $f$ is assumed to be 0.2 (20%).
Projected Infrastructure Utilization \( f[\text{Infrastructure}] = \text{Recent Utilization } f[\text{Infrastructure}] \times (1 + \text{Forecast Horizon - Infrastructure} \times \text{Expected Growth in Utilization } f[\text{Infrastructure}]) \)

Units: dmnl

The Projected level of Infrastructure Utilization of infrastructure \( f \) is forecast as the Recent Utilization of infrastructure \( f \), multiplied by one plus the Expected Growth in Utilization of infrastructure \( f \), multiplied by the Forecast Horizon for Infrastructure.

Expected Growth in Utilization \( f[\text{Infrastructure}] = \text{SMOOTH(Indicated Utilization Growth Rate } f[\text{Infrastructure}], \text{Time to Perceive Infrastructure Growth)} \)

Units: dmnl/year

The expected growth in utilization of infrastructure \( f \) is given by the exponential smoothing of the Indicated Utilization Growth Rate, smoothed over the Time to Perceive Infrastructure Growth.

Time to Perceive Infrastructure Growth\(=1 \)
Units: year

The Time to Perceive Infrastructure Growth is assumed to be 1 year.

Indicated Utilization Growth Rate \( f[\text{Infrastructure}] = \text{TREND(Recent Utilization } f[\text{Infrastructure}], \text{Historic Time Horizon for Infrastructure Growth), 0) \)

Units: dmnl/year

The Indicated Utilization Growth Rate is the average rate of fractional growth in Recent Utilization, calculated over the Historic Time Horizon for Infrastructure Growth.

Historic Time Horizon for Infrastructure Growth\(=1 \)
Units: year

The Historic Time Horizon for forecasting Infrastructure Growth is assumed to be 1 year.

Recent Utilization \( f[\text{Infrastructure}] = \text{SMOOTH(Infrastructure Utilization } f[\text{Infrastructure}], \text{Infrastructure Perception Time}) \)

Units: dmnl

The recent rate of utilization of infrastructure \( f \) is given by the exponential smoothing of the current rate of Infrastructure Utilization, smoothed over the Infrastructure Perception Time.

Infrastructure Perception Time\(=1 \)
Units: year

The time to perceive the rate of Recent Utilization is assumed to be 1 year.

Infrastructure Utilization \( f[\text{Infrastructure}] = \text{IF THEN ELSE( Demand for Infrastructure } f[\text{Infrastructure}] > 0 \text{, } \text{ZIDZ(Demand for Infrastructure } f[\text{Infrastructure}], \text{Available Infrastructure } f[\text{Infrastructure}]), 0) \)

Units: dmnl

If the quantity of Available Infrastructure is greater than zero, the level of Infrastructure Utilization of infrastructure \( f \) is calculated as Demand for Infrastructure \( f \), divided by Available Infrastructure \( f \).

Demand for Infrastructure \( f[\text{Infrastructure}] = \text{SUM(Demand for Infrastructure by Platform } i[\text{Technology,Infrastructure}]) \)

Units: stations

The total demand for refueling stations of infrastructure \( f \) is the sum of demand for infrastructure \( f \) from each vehicle platform \( i \).

Demand for Infrastructure by Platform \( i[\text{Technology,Infrastructure}] = \text{ZIDZ("Fleet Refuels per Year by Platform-Fuel \( i\)"[Technology,Infrastructure],Refuels per Station per Year \( i\)[Technology,Infrastructure])} \)

Units: stations

205
The demand for refueling stations of infrastructure \( f \) by vehicle platform \( i \) is calculated as the refuels per year using infrastructure \( f \) demanded by the installed base of platform \( i \) vehicles (Fleet Refuels per Year by Platform-Fuel), divided by the number of refuels per year that a station of infrastructure \( f \) is able to deliver to vehicle platform \( i \) (Refuels per Stations per Year).

\[
\text{"Fleet Refuels per Year by Platform-Fuel if Technology,Infrastructure"} = \frac{\text{Refuels per Year if Technology,Infrastructure}}{\text{Installed Base if Technology}} \\
\text{Units: vehicles/year}
\]

The total Fleet Refuels per Year by Platform \( i \) using Fuel \( f \) is calculated as the number of Refuels per Year demanded by each vehicle of platform \( i \) using infrastructure \( f \), multiplied by the Installed Base of vehicles of platform \( i \).

\[
\text{Refuels per Station per Year if Technology,Infrastructure}=\text{ZIDZ(Operating Hours per Year if Infrastructure,Refueling Time if Technology,Infrastructure)}*\text{Pumps per Station if Infrastructure} \\
\text{Units: vehicles/stations/year}
\]

The Refuels per Station per Year possible by a station of infrastructure \( f \) refueling a vehicle of platform \( i \) is calculated as the number of Operating Hours per Year the station is open, divided by the Refueling Time of platform \( i \) using infrastructure \( f \), multiplied by the number of pumps available at that station.

\[
\text{Operating Hours per Year if Infrastructure}=3140.8760 \\
\text{Units: hour/year/stations}
\]

It is assumed that each gasoline station is open 3,140 hours per year, while each electric recharging point is always open, that is, open 8,760 hours per year.

\[
\text{Pumps per Station if Infrastructure}=10,1 \\
\text{Units: dmnl}
\]

It is assumed that each gasoline station has 10 pumps, while each recharging station only has a single recharging point.

\[
\text{Refueling Time if [GAS,Infrastructure]=IF THEN ELSE (Infrastructure=GASPUMP, Transaction Time+(Fuel Fill i[GAS]/Fuel Pumping Rate),0)} \\
\text{Refueling Time if [HEV,Infrastructure]=IF THEN ELSE (Infrastructure=GASPUMP, Transaction Time+(Fuel Fill i[PHEV40]/Fuel Pumping Rate),0)} \\
\text{Refueling Time if [PHEV40,Infrastructure]=IF THEN ELSE (Infrastructure=PLUG, Transaction Time+(Battery Recharge i[PHEV40]/Battery Recharging Rate),0)} \\
\text{Refueling Time if [BEV,Infrastructure]=IF THEN ELSE (Infrastructure=PLUG, Transaction Time+(Battery Recharge i[BEV]/Battery Recharging Rate),0)} \\
\text{Units: hour/vehicles}
\]

For each vehicle platform \( f \) refueling from infrastructure \( i \), the Refueling Time for each refueling event is calculated as the Transaction Time plus the quantity of fuel being delivered (Fuel Fill for gasoline or Battery Recharge for electricity), divided by the rate at which that fuel is delivered (Fuel Pumping Rate for gasoline or Battery Recharging Rate for electricity).

\[
\text{Fuel Fill i[GAS]}=\text{ZIDZ(Effective Range if[GAS,GASPUMP],FE by Platform i[GAS])} \\
\text{Fuel Fill i[HEV]}=\text{ZIDZ(Effective Range if[HEV,GASPUMP],FE by Platform i[HEV])} \\
\text{Fuel Fill i[PHEV40]}=\text{ZIDZ(Effective Range if[PHEV40,GASPUMP],FE by Platform i[PHEV40])} \\
\text{Fuel Fill i[BEV]}=0 \\
\text{Units: gallon/vehicles}
\]

The quantity of gasoline delivered per refueling event differs by platform. For the BEV platform which only recharges with electricity, Fuel Fill = 0. For the GAS, HEV and PHEV platforms, the quantity of gasoline delivered is calculated as the Effective Range of the platform (miles) divided by the fuel economy of the platform (miles/gallon).

\[
\text{Battery Recharge if [GAS]}=0 \\
\text{Battery Recharge if [HEV]}=0 \\
\text{Battery Recharge if [PHEV40]}=\text{Effective Range if[PHEV40,PLUG]*EE by Platform i[PHEV40]} \\
\text{Battery Recharge if [BEV]}=\text{Effective Range if[BEV,PLUG]*EE by Platform i[BEV]} \\
\text{Units: kW*hour/vehicles}
\]
The quantity of battery recharging differs by platform. For the GAS and HEV platforms which cannot recharge directly, Battery Recharge = 0. For the plug-in PHEV and BEV platforms, the quantity of battery recharging per recharging event is calculated as the Effective Range of the platform using electricity (miles), multiplied by the energy efficiency of the platform (kilowatt-hours per mile).

Fuel Pumping Rate=600
Units: gallon/hour

The gasoline pumping rate is assumed to be 600 gallons per hour.

Battery Recharging Rate=7.2
Units: kW

The rate of electric vehicle battery recharging is assumed to be 7.2 kilowatts.

Transaction Time=0.0833
Units: hour/vehicles

The transaction time incurred with each refueling event (to connect / disconnect the vehicle to the infrastructure and pay for fuel) is assumed to be 0.0833 hours (5 minutes).

**Learning-by-Doing and R&D**

Base Vehicle Cost i[Technology]=IF THEN ELSE(SW Learning=0, Initial Base Vehicle Cost i[Technology], Initial Base Vehicle Cost i[Technology]((1-((1-Effect of Experience on Base Vehicle Cost i[Technology])*"Weight Experience v R&D i"[Technology]))^"Effect of R&D on Base Vehicle Cost i"[Technology])*"Weight Experience v R&D i"[Technology])*(1-((1-"Effect of R&D on Base Vehicle Cost i"[Technology])*"Weight Experience v R&D i"[Technology])))
Units: $/vehicles

The cost of each vehicle system reduces with cost-reductions achieved through production experience and R&D. Here I use the example of the base vehicle subsystem to demonstrate these dynamics. The cost of the base vehicle is equal to the Initial Base Vehicle Cost for platform j in year 2000, multiplied by the Effect of Experience on Base Vehicle Cost and the Effect of R&D on Base Vehicle Cost, where these two effects are weighted according to the emphasis placed on these alternative sources of cost-reductions within automotive manufacturers.

Initial Base Vehicle Cost i[Technology]=15000
Units: $/vehicles

The initial cost of the base vehicle for all platforms is assumed to be $15,000.

"Weight Experience v R&D i"[Technology]=0.5
Units: dmnl

It is assumed that automakers focus on learning from production experience and R&D equally. Hence, Weight Experience v R&D for platform i is assumed to take the value 0.5.

Effect of Experience on Base Vehicle Cost i[Technology]=(("Cumulative Experience - Base Vehicle i"[Technology])/Initial Experience Base Vehicle i[Technology])^"Experience Beta"
Units: dmnl

Cost-reductions that result from production experience are modeling using a standard power-law. The Effect of Experience on Base Vehicle Cost is estimated as the ratio of Cumulative Experience with the Base Vehicle subsystem for platform i, relative to the Initial Experience with the Base Vehicle subsystem for platform i, raised to the power of the negative of the Experience Beta.

Experience Beta=-LOG(Learning Curve Strength, 2)
Units: dmnl
The Experience Beta parameter in the power-law is calculated as the negative of the log base 2 of the Learning Curve Strength improvement ratio.

Learning Curve Strength=0.85
Units: dmnl

The learning curve strength (improvement ratio) is assumed to be 0.85, representative of a 15% reduction in subsystem costs with each doubling in cumulative experience.

Initial Experience Base Vehicle i[Technology]=1e+09
Units: vehicles

Initial cumulative experience with the base vehicle subsystem for platform j is assumed to be 1 billion vehicles, building on the extensive experience automotive manufacturers have from the conventional GAS platform.

"Cumulative Experience - Base Vehicle i[Technology]= INTEG ("Experience Gain - Base Vehicle i[Technology],Initial Experience Base Vehicle i[Technology])
Units: vehicles

Cumulative production experience with the base vehicle subsystem for platform j accumulates annual production experience, initially taking the value given by the variable Initial Experience Base Vehicle.

"Experience Gain - Base Vehicle i[TechnologyTo]=SUM(Effective Base Vehicle Spillover Matrix ij[Technology],TechnologTo]*Order Fulfillment j[Technology]!"(1-"R&D Share (vs Learning) i[TechnologyTo]"*Learning Share i[TechnologyTo,BASEVEH])
Units: vehicles/year

The experience gain in the base vehicle subsystem of platform i is the sum of the product of the Effective Base Vehicle Spillover Matrix multiplied by experience gained in each platform j, summing across spillover platforms. The experience gained in each platform is the product of the rate of Order Fulfillment (noting that sales is used as a proxy for experience) multiplied by the fraction of technology change that comes from learning, multiplied by the share of learning effort that is concentrated on the base vehicle subsystem compared with other vehicle subsystems.

Effective Base Vehicle Spillover Matrix ij[Technology,TechnologyTo]=IF THEN ELSE (Technology=TechnologyTo, 1, Extent of Platform Cost Reduction Spillovers)
Units: dmnl

The Effective Base Vehicle Spillover Matrix defines the extent to which experience gained in the base vehicle subsystem spills over between platforms. If platform i = platform j, the Spillover Matrix takes the value 1, capturing the direct effect of production experience with platform j. Otherwise, the Spillover Matrix takes the value given by the variable Extent of Platform Cost Reduction Spillovers.

Extent of Platform Cost Reduction Spillovers=0
Units: dmnl

The extent of platform cost-reduction spillovers is assumed to be 0 initially. This assumption is explored in Scenario 4.

"Effect of R&D on Base Vehicle Cost i[Technology]=ZIDZ("Cumulative R&D Base Vehicle i[Technology],"Initial R&D Base Vehicle i[Technology])^-"R&D Beta"
Units: dmnl

Cost-reductions that result from R&D are modeling using a standard power-law. The Effect of R&D on Base Vehicle Cost is estimated as the ratio of Cumulative R&D with the Base Vehicle subsystem for platform i, relative to the Initial R&D with the Base Vehicle subsystem for platform i, raised to the power of the negative of the R&D Beta.

"R&D Beta"=-LOG(Learning Curve Strength, 2)
Units: dmnl

The R&D Beta parameter in the power-law is assumed to be the same as the Learning Beta, calculated as the negative of the log base 2 of the Learning Curve Strength improvement ratio.
"Initial R&D Base Vehicle i"[Technology]=1e+10
Units: $

Initial cumulative R&D spending on the base vehicle subsystem for platform i is assumed to be $10 billion, building on the extensive experience the automotive industry has building conventional GAS vehicles.

"Cumulative R&D Base Vehicle i"[Technology]= INTEG ("R&D Spending Base Vehicle i"[Technology],
"Initial R&D Base Vehicle i"[Technology])
Units: $

Cumulative R&D spending on the base vehicle subsystem for platform i accumulates annual R&D spending on the base vehicle subsystem, initially taking the value of the variable Initial R&D Base Vehicle.

"R&D Spending Base Vehicle i"[Technology]= SUM(Effective Base Vehicle Spillover Matrix
ij[TechnologyTo!,Technology]*"R&D Budget ia"[Technology,BASEVEH])
Units: $/year

R&D spending on the base vehicle subsystem for platform i is the sum of the product of the Effective Base Vehicle Spillover Matrix, multiplied by the amount spent on R&D for the base vehicle subsystem in platform i, the R&D Budget, summing across spillover platforms j.

**Accounting - Energy Prices**

Effective Gas Price=Gas Price+Carbon Cost per Gallon
Units: cents/gallon

The effective price of gasoline (cents/gallon) is calculated as the price of gasoline (Gas Price) plus the carbon cost per gallon of gasoline, if any.

Units: cents/gallon

The gas price is assumed to increase linearly over time, from the price of gasoline in year 2000 to the price of gasoline in year 2050, increasing over the Ramp Duration time.

2000 Gas Price=150
Units: cents/gallon

The price of gasoline in year 2000 is assumed to be 150 cents/gallon ($1.50/gallon).

"2050 Gas Price"=400
Units: cents/gallon

The price of gasoline in year 2000 is assumed to be 150 cents/gallon ($1.50/gallon).

Ramp Duration=50
Units: year

The increase in gasoline price is assumed to occur over 50 years (year 2000 to year 2050).

Carbon Cost per Gallon=Current Carbon Price*Cents per Dollar*"GHG Emissions Factor - Gasoline"
Units: cents/gallon

The Carbon Cost per Gallon (cents/gallon) that results from the implementation of a carbon price is calculated as the Current Carbon Price ($/tonne CO2e), converted to cents/tonne CO2e, multiplied by the GHG emissions factor for gasoline (tonnes CO2e per gallon) which captures the carbon content of each gallon of gasoline.

Effective Electricity Price=Electricity Price+Carbon Cost per kWh
Units: cents/(kWh*hour)
The effective price of electricity (cents/kilowatt-hour) is calculated as the price of electricity (Electricity Price) plus the carbon cost per kilowatt-hour of electricity, if any.


Units: cents/(kW*hour)

The electricity price is assumed to increase linearly over time, from the price of electricity in year 2000 to the price of electricity in year 2050, increasing over the Ramp Duration time. The Renewable Electricity Price Premium is added if plug-in EVs are recharging with 100% renewable electricity, indicated by SW Electricity Source=1.

"2000 Electricity Price"=11.09
Units: cents/(kW*hour)

The average of price of conventional grid electricity is assumed to be 11.09 cents/kilowatt-hour (EIA 2012).

"2050 Electricity Price "=11.09
Units: cents/(kW*hour)

The average price of conventional grid electricity is assumed to remain constant between year 2000 and year 2050.

Renewable Electricity Price Premium=2
Units: cents/(kW*hour)

The price premium for the purchase of electricity from renewable generation sources is assumed to be 2 cents/kilowatt-hour.

Carbon Cost per kWh=Current Carbon Price*Cents per Dollar*"GHG Emissions Factor - Electricity"
Units: cents/(kW*hour)

The Carbon Cost per kWh (cents/kilowatt-hour) that results from the implementation of a carbon price is calculated as the Current Carbon Price ($/tonne CO2e), converted to cents/tonne CO2e, multiplied by the GHG emissions factor for electricity (tonnes CO2e per kilowatt-hour) which captures the carbon content of each kilowatt-hour of electricity.

Current Carbon Price=RAMP( (Carbon Price/Carbon Price Ramp Duration), Carbon Price Start Year, Carbon Price Start Year+Carbon Price Ramp Duration )
Units: $/tonnes CO2e

The Current Carbon Price is assumed to increase linearly from the Carbon Price Start Year to the end year calculated as the Carbon Price Start Year plus the Carbon Price Ramp Duration.

Carbon Price Start Year=2015
Units: year

The carbon price applied in Scenario 8 is assumed to commence its phase-in in year 2015.

Carbon Price Ramp Duration=15
Units: year

The carbon price applied in Scenario 8 is assumed to phase-in over 15 years.

Carbon Price=150
Units: $/tonnes CO2e

The carbon price applied in Scenario 8 is assumed to take the value $150/tonne CO2e when the phase-in is completed.

Cents per Dollar=100
Units: cents/$

The units conversion Cents per Dollar is used to convert between cents and dollars.
**Accounting - Greenhouse Gas Emissions**

Annual Emissions by Platform $i$[$\text{Technology}$] = Annual Manufacturing Emissions by Platform $i$[$\text{Technology}$] + Annual Operating Emissions by Platform $i$[$\text{Technology}$] + Annual Recycling/Disposal Emissions by Platform $i$[$\text{Technology}$]

Units: tonnes CO2e/year

Annual greenhouse gas emissions from platform $j$ are calculated as the sum of GHG emissions from manufacturing of new vehicles for platform $j$, the GHG emissions from operating vehicles of platform $j$, and the GHG emissions from the recycling/disposal of vehicles from platform $j$.

Annual Manufacturing Emissions by Platform $i$[$\text{Technology}$] = Vehicle Manufacturing $i$[$\text{Technology}$] + Battery Manufacturing $i$[$\text{Technology}$]

Units: tonnes CO2e/year

Annual emissions from manufacturing vehicles for platform $i$ is estimated as the annual emissions from manufacturing base vehicles for technology $i$, plus annual emissions from manufacturing traction batteries for technology $i$.

Vehicle Manufacturing $i$[$\text{Technology}$] = GHG Emissions per Vehicle Manufactured * Order Fulfillment $i$[$\text{Technology}$]

Units: tonnes CO2e/year

Annual emissions from manufacturing base vehicles for platform $i$ is calculated as the tonnes of CO2-e emitted per vehicle manufactured, multiplied by the number of platform $i$ vehicles sold each year.

Battery Manufacturing $i$[$\text{Technology}$] = Battery $i$[$\text{Technology}$] * Order Fulfillment $i$[$\text{Technology}$] * GHG Emissions per Unit Battery Manufactured

Units: tonnes CO2e/year

Annual emissions from manufacturing traction batteries for platform $i$ is calculated as the tonnes of CO2-e emitted per kilowatt-hour of battery manufactured, multiplied by the quantity of batteries (in kilowatt-hours) deployed in vehicle of platform $i$, multiplied by the number of platform $i$ vehicles sold each year.

GHG Emissions per Vehicle Manufactured = 8.5

Units: tonnes CO2e/vehicle

It is assumed that 8.5 tonnes of CO2e are emitted for each base vehicle manufactured (Samaras and Meisterling 2008).

GHG Emissions per Unit Battery Manufactured = 0.12

Units: tonnes CO2e/(kW*hour)

It is assumed that 0.12 tonnes of CO2e are emitted for each kilowatt-hour of traction battery manufactured (Samaras and Meisterling 2008).

Annual Operating Emissions by Platform $i$[$\text{Technology}$] = Annual Miles by Platform $i$[$\text{Technology}$] * Emissions per Mile $i$[$\text{Technology}$]

Units: tonnes CO2e/year

The annual GHG emissions resulting from operation of each vehicle of platform $i$ is calculated as the annual number of miles driven by platform $i$ vehicles, multiplied by the GHG emissions per mile traveled by platform $i$ vehicles.

Annual Miles by Platform $i$[$\text{Technology}$] = Installed Base $i$[$\text{Technology}$] * VMT per Year $i$[$\text{Technology}$]

Units: miles/year

The annual number of miles traveled by all vehicles of platform $i$ is calculated as the number of platform $i$ vehicles (Installed Base) multiplied by the annual number of miles driven by each platform $i$ vehicle.

Emissions per Mile $i$[$\text{Technology}$] = ("% All Electric Miles by Installed Base Platform $i$[$\text{Technology}$] * Emissions per Mile Electric $i$[$\text{Technology}$]) + ((1 - "% All Electric Miles by Installed Base Platform $i$[$\text{Technology}$]) * Emissions per Mile Gasoline $i$[$\text{Technology}$])

Units: tonnes CO2e/miles

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The average Emissions per Mile for technology $i$ is the weighted average of the emissions per mile from platform $i$ using electricity, and the emissions per mile from platform $i$ using gasoline, weighted according to the percentage of electric miles driven by technology $i$.

Emissions per Mile Gasoline $i[Technology]$ = $ZIDZ(\text{"GHG Emissions Factor - Gasoline"}, FE \text{ by Platform } i[Technology])$

Units: tonnes CO2e/miles

Emissions per mile (tonnes CO2e/mile) traveled using gasoline for platform $i$ is calculated as the GHG emissions factor of gasoline (tonnes CO2e/gallon) divided by the fuel economy of platform $i$ (miles/gallon).

Emissions per Mile Electric $i[Technology]$ = $\text{"GHG Emissions Factor - Electricity"} \times EE \text{ by Platform } i[Technology]$

Units: tonnes CO2e/miles

Emissions per mile (tonnes CO2e/mile) traveled using electricity for platform $i$ is calculated as the GHG emissions factor of electricity (tonnes CO2e/kilowatt-hour) multiplied by the electric energy efficiency of platform $i$ (kilowatt-hour/mile).

"GHG Emissions Factor - Gasoline" = 0.00891
Units: tonnes CO2e/gallon

The carbon intensity of gasoline is assumed to be 0.00891 tonnes CO2e/gallon of gasoline (EPA 2012).

"GHG Emissions Factor - Electricity" = IF THEN ELSE(SW Electricity Source = 0, "GHG Emissions Factor - Grid Mix", "GHG Emissions Factor - Renewables")
Units: tonnes CO2e/(kW*hour)

The carbon intensity of the electricity used for EV recharging is equal to the carbon intensity of the grid mix (GHG Emissions Factor - Grid Mix) if SW Electricity Source $= 0$, and the carbon intensity of renewable electricity otherwise (GHG Emissions Factor - Renewables).

"GHG Emissions Factor - Renewables" = 0
Units: tonnes CO2e/(kW*hour)

The carbon intensity of electricity generation from renewable technologies is assumed to be 0.

"GHG Emissions Factor - Grid Mix" = 0.000684
Units: tonnes CO2e/(kW*hour)

The carbon intensity of electricity generation from the current mix of electricity generation technologies on the US grid is assumed to be 0.000684 tonnes CO2e/kilowatt-hour (EPA 2012).

SW Electricity Source = 0
Units: dmnl

SW Electricity Source is a binary flag, taking the value 0 if conventional grid electricity is used for plug-in EV recharging, and taking the value 1 if 100% renewable electricity is used.

Units: tonnes CO2e/year

Annual emissions from recycling/disposing of vehicles of platform $i$ is calculated as the tonnes of CO2-e emitted per vehicle retired, multiplied by the number of platform $i$ vehicles retired each year.

GHG Emissions per Vehicle Retired = 1.14
Units: tonnes CO2e/vehicles

It is assumed that 1.14 tonnes CO2e are emitted when each vehicle is recycled/disposed (Notter, Marcel Gauch et al. 2010).