An agent-based model to study market penetration of plug-in hybrid electric vehicles

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ABSTRACT

A spatially explicit agent-based vehicle consumer choice model is developed to explore sensitivities and nonlinear interactions between various potential influences on plug-in hybrid vehicle (PHEV) market penetration. The model accounts for spatial and social effects (including threshold effects, homophily, and conformity) and media influences. Preliminary simulations demonstrate how such a model could be used to identify nonlinear interactions among potential leverage points, inform policies affecting PHEV market penetration, and help identify future data collection necessary to more accurately model the system. We examine sensitivity of the model to gasoline prices, to accuracy in estimation of fuel costs, to agent willingness to adopt the PHEV technology, to PHEV purchase price and rebates, to PHEV battery range, and to heuristic values related to gasoline usage. Our simulations indicate that PHEV market penetration could be enhanced significantly by providing consumers with ready estimates of expected lifetime fuel costs associated with different vehicles (e.g., on vehicle stickers), and that increases in gasoline prices could nonlinearly magnify the impact on fleet efficiency. We also infer that a potential synergy from a gasoline tax with proceeds is used to fund research into longer-range lower-cost PHEV batteries.

1. Introduction

Plug-in hybrid electric vehicles (PHEVs) have many potential advantages over conventional vehicles, but it is not clear what combinations of policies will be most cost-effective in promoting successful market penetration of this new vehicle technology. The intent of this article is to (a) present a framework for a novel agent-based vehicle consumer choice model, (b) illustrate how such a model could be used by policy-makers and vehicle manufacturers to help prioritize investments influencing PHEV adoption, and (c) identify additional empirical evidence that will be necessary to improve the predictive power of such a model. To motivate this work, we first review potential PHEV advantages, hurdles to PHEV market penetration, and related agent-based models.

A recent joint report by the Electric Power Research Institute (EPRI) and the Natural Resources Defense Council (NRDC) (Duvall et al., 2007) found that PHEVs have the potential to substantially reduce greenhouse gas emissions. From a consumer perspective, PHEVs offer the higher fuel efficiency of electric vehicles (EVs) within the all-electric range, but also the convenience and flexibility of traditional fuels and existing refueling infrastructure for longer trips. Since vehicles travel on average at around 23 miles per day (37 km/day) in the U.S. (Bose et al., 2003), the majority of daily travel should be within the all-electric battery range of the most first-generation PHEV vehicles, anticipated to be about 30–60 miles (50–100 km), assuming recharging is available on a daily basis. Lifecycle analyses reported by Jaramillo et al. (2009) indicate PHEV greenhouse gas emissions to be about half of that of current gasoline and diesel motor fuels, even when using coal-fired electricity generation, assuming CO_2 capture and storage. Similar conclusions are reached in a study by Smith (2010) on the potential use of PHEVs in the automotive fleet in Ireland.

As primary power sources for the electric grid become greener and gasoline prices increase, emission reductions and fuel savings with PHEVs will even be greater. A projected lifecycle analysis for the year 2030 by Offer et al. (2010) compares PHEVs with battery–electric vehicles, hydrogen fuel-cell vehicles, and internal combustion vehicles. The study finds that the PHEV and battery–electric options offer much lower lifecycle costs than either the fuel-cell or internal combustion vehicle options. Widespread PHEV adoption would have the added benefit of substantially increasing the potential net electrical energy storage capacity in a community, which could increase the stability of the power system. For instance, Anderson et al. (2009) and Andersson et al. (2010) propose development of a vehicle-to-grid system, whereby electric vehicles would be used to store and release energy for the electrical power grid that

would serve to even out the peaks and valleys inherent in electrical energy usage and the fluctuating supply typical of renewable energy sources (such as wind).

Despite these potential advantages, there remain significant barriers to widespread adoption of new PHEV technology. In a 2008 survey of U.S. consumers, 69% of respondents reported little or no familiarity with PHEV technology (Axsen and Kurani, 2008), although in a 2010 survey over half of the respondents reported some awareness of the Chevrolet Volt (Zypryme Research and Consulting, 2010). Many consumers are hesitant to adopt unfamiliar technologies, and there may be significant consumer uncertainty about issues such as battery life, replacement costs, and recharging time (Sovacool and Hirsh, 2009; Zypryme Research and Consulting, 2010). Uncertainties in future petroleum prices and challenges in estimating fuel usage for different trip lengths make it difficult for consumers to accurately estimate the financial and/or environmental PHEV trade-offs relative to other vehicles. Studies based on data for consumer purchases of hybrid electric vehicles (HEVs) (Heffner et al., 2007; Turrentine and Kurani, 2007; Griskevicius et al., 2010) support the conclusion that most consumers elect to purchase HEVs for non-financial reasons, (e.g., to symbolize their commitment to reducing gasoline consumption, to reduce greenhouse gas emissions, to reduce dependence on foreign oil), rather than on detailed rational financial analyses of lifetime costs. In any case, HEVs are not currently a cost-efficient choice; a recent study by the British Columbia Automobile Association (BCAA, 2010) found that 15 of the 16 HEVs studied did not yield even a 5-year payback at 2010 Canadian gasoline prices (higher than U.S. gasoline prices), when compared to their similar gasoline vehicle (GV) counterparts (the one exception was an expensive luxury HEV).

A wide variety of governmental regulations and incentives have been proposed or implemented to accelerate market penetration of PHEVs (www.afdc.energy.gov/afdc). Morrow et al. (2010) discuss the effects of fuel taxes, increases in fuel economy standards, and purchase tax credits for fuel-efficient vehicles. They examine the sensitivity of fuel-efficient vehicle purchases using these approaches and predictions of the U.S. Energy Information Administration's National Energy Modeling System. They find that, in general, purchase tax credits are expensive and ineffective at reducing emissions, whereas the most effective approach for increasing fuel efficiency is to increase gasoline costs. Skerlos and Winebrake (2010) examined the impact of tax credits for PHEV purchase, which were introduced in 2009 by the U.S. government and are available to all consumers equally in all parts of the country. The authors argue that these tax credits would be more effective if targeted in certain geographic locations where PHEV technology offers maximum benefit, and if they were dependent on consumer income. Diamond (2009) examined the relationship between hybrid adoption rates and governmental incentive policies in different U.S. states. His findings similarly indicate a strong relationship between hybrid adoption and gasoline price, but a much weaker relationship between hybrid adoption and government incentives.

While studies based on past data trends for HEVs and other fuel-efficient vehicles provide relevant insight, they are of limited applicability for estimating consumer response to the very different conditions associated with current-day adoption of PHEV technology. The plug-in technology offers new challenges to market penetration, and environmental attitudes and awareness are also very different than those in past decades. While awareness of the role of vehicle emissions in global climate change is high in many parts of the world, it is not clear how consumers will weigh a vehicle's heuristically perceived benefits against rational financial considerations when making a vehicle-purchasing decision. Consumer choices are not necessarily based on financially accurate assessments of alternatives (Turrentine and Kurani, 2007), and values that affect consumer choices are often influenced by media and social networks (Yin, 1999; Newig and Hesselmann, 2004; Pew Research Center for the People and the Press, 2009). Traditional discrete-choice models assume a static distribution of decision strategies and do not support consumer behavior changes in response to social or other external pressures. However, recent variations of discrete-choice models have been proposed that demonstrate the importance of social or psychological factors (Bolduc et al., 2008) and 'neighbor effects' on consumer attitudes as the market share of a given vehicle type grows (Mau et al., 2008).

Agent-based models (ABMs) stochastically simulate spatially explicit interactions and behaviors of autonomous and heterogeneous agents in order to observe and study the emergence of coherent (but dynamic) system behaviors at larger spatial and temporal scales. ABMs have become increasingly popular in studies of transportation logistics and traffic flow (Dia, 2002; Henesey et al., 2005). In a particularly relevant ABM, Mueller and de Haan (2009) studied the influence of incentives on car purchases and the effect of feebate approaches to encourage purchase of high energy efficiency vehicles (de Haan et al., 2009). In another relevant PHEV market penetration ABM (Sullivan et al., 2009), vehicle preferences depend on size, performance, and brand, with the proviso that they must stay within their monthly budgets. Consequently, PHEV penetration is shown to be strongly dependent on permanent PHEV tax rebates, subsidies, and sales tax exemptions.

In this article, we present an ABM of heterogeneous interacting vehicle consumer agents that accounts for correlated demographic agent variability as well as several unique spatial and social effects. We examine the effects of (i) gasoline prices, (ii) ability of agents to consider fuel costs, (iii) PHEV purchase price and rebates, (iv) PHEV all-electric battery range, (v) consumer values regarding financial vs. non-financial concerns in vehicle purchase, (vi) agent comfort thresholds with the PHEV technology, and (vii) social and media influences on PHEV market penetration and fuel efficiency of the resulting fleet after 25 years. Preliminary insights gained from our results and potential model uses for informing energy and transportation policy are discussed.

2. Agent-based model

In the model implementation presented herein we make several simplifying assumptions, due in large part to low model sensitivity to specific details or a lack of empirical data that could justify a more complex model. For example, we currently assume that each agent's age and social network are static; we model individual consumers rather than households; we assume uniform daily driving patterns and availability of daily recharging; and we model only a small subset of vehicle options. Despite these limiting assumptions, exploration of model sensitivities provides useful insights into qualitative system behavior and interactions between potential leverage points. As more data become available, the model framework can easily accommodate more realistic assumptions and vehicle options.

Vehicle consumers weigh the costs and benefits of many vehicle characteristics in addition to fuel type, such as seating capacity, cargo capacity, safety, reliability, and drive train, when determining which vehicle to purchase. We originally considered modeling a two-step decision process similar to that employed by Mueller and de Haan (2009). The first step would involve a screening process that identifies which different models fit some basic set of desired attributes (other than fuel type), followed by a cost-benefit analysis between the remaining models. However,

this approach requires speculation on the specifications of a wide range of hypothetical PHEVs not yet available. While the first-generation PHEVs are largely compact vehicles, it is reasonable to assume that, as PHEV technology matures, many comparable vehicle types will become available with and without a plug-in option. In this case, regardless of other consumer preferences, the decision reduces to whether or not to purchase the plug-in option. For these reasons, and to control our study variables, we have opted here to focus on modeling the subset of potential new-car buyers (agents) who have narrowed their choice to one of the three compact vehicles: a gas vehicle (GV), a hybrid electric vehicle (HEV), or a plug-in hybrid electric vehicle (PHEV), which are otherwise similar in all characteristics except fuel type, fuel efficiency, and purchase price. In our model, differences in fuel efficiency can impact both rational financial considerations (if an agent is provided with a rational estimate of fuel savings) and other heuristic considerations (such as financially irrational guesses on fuel savings or a desire to reduce greenhouse gas emissions, oil spills, or dependence on foreign oil) related to vehicle choice, although different agents weight these differently.

2.1. Agent attributes

Each consumer agent in the ABM has several associated attributes including age, annual salary, residential location, typical years of car ownership (Y), annual vehicle miles traveled (VMT), and vehicle age, fuel type, and fuel economy of their current vehicle, including all-electric range (if any) and miles per gallon (MPG) when not in all-electric mode. In addition, each agent has an associated "spatial neighborhood", a "social network", a threshold (T) of perceived PHEV market share over which they are willing to consider adopting the PHEV technology, and a level of rationality (R) of how (if at all) they estimate projected fuel costs. Surveys indicate that many consumers express a willingness to pay a price premium for a more fuel-efficient vehicle (Turrentine and Kurani, 2007; Zypryme Research and Consulting, 2010), may irrationally overestimate potential fuel savings (Turrentine and Kurani, 2007), and that non-financial reasons related to the environment, energy, and attraction to new technology can play a large role in consumer willingness to purchase an HEV (Turrentine and Kurani, 2007), EV, or PHEV (Zypryme Research and Consulting, 2010). We model this through an agent attribute G, which indicates how much weight the agent places on heuristically perceived benefits related to saving gasoline that are independent of rationally estimated financial benefits (i.e., G can be interpreted to account for a desire to reduce greenhouse gas emissions, oil spills, or dependence foreign oil, as well as irrationally estimated savings in fuel costs). For simplicity, most agent attributes are treated as static, and all financial costs are computed in inflation-adjusted 2009 U.S. dollars brought to net present value. The only agent attributes that can change during a simulation are (a) the heuristic weight G, which can change dynamically due to social and media influences (although agent susceptibilities to such influences are heterogeneous) and (b) current vehicle ownership (and associated vehicle attributes, including vehicle age). External forces modeled as dynamic (time series) data are the intensity of media coverage related to the need to reduce gasoline consumption, gasoline prices, and electricity prices. Rather than allowing dynamic changes in the ability of an agent to consider rationally estimated fuel costs or allowing R to take on values other than 0 or 1 (as done in an earlier version of the model; see Pellon et al., 2010), we have opted to treat R as a binary control parameter so that we can methodically explore the sensitivity of model results to this important attribute.

In Section 2.2 we outline how these (and other) attributes are used in the decision-making process. In Section 2.3 we discuss constraints on these attributes and our initialization of them in the reported experiments. For readability, we do not explicitly subscript agent or vehicle attributes in the text, but it should be understood that these have different values for different agents and vehicles in the model.

2.2. Agent decision-making

In the ABM, agents are asynchronously updated during each simulated year according to the flowchart of Fig. 1. We apply agent updates uniformly throughout the year in random agent order. The numbered steps in Fig. 1 are explained in more detail below.

Both media coverage and social interactions influence consumer attitudes toward the environment (Yin, 1999; Newig and Hesselmann, 2004; Pew Research Center for the People and the Press, 2009). Consequently, in step 1, we allow the agent's value for the heuristic weight G to be increased or decreased due to media and/or social influences, as follows. The intensity of media coverage (M) that conveys the need to reduce gasoline and energy consumption is modeled as a daily time series of real numbers between 0 and 1; we define 'media coverage' broadly to include such things as current events (such as global climate change, major oil spills, and foreign wars with connections to oil resources), public service announcements (PSAs), and 'green' advertising of fuel-efficient vehicles. All agents are exposed to the same daily media coverage; however, the average annual change in media coverage ΔM leading up to the day each agent considers buying a car differs. Based on the assumption that changes in media coverage can influence attitudes over time, each agent's value for G is adjusted based on the agent's personal susceptibility (S_M) to media influence as follows:

$$G = G + \Delta M \times S_M \tag{1}$$

Each agent also has a social network comprising other agents of similar age, salary, and residential location (within a given agent-specific distance). Each year, with probability specified by the agent's susceptibility to social influence (S_S), the agent assesses whether its heuristic weight G is above or below the median of the G values of those in its social network. If above (below), one "friend" is selected at random (to simulate stochastic social influences) from the half of the agent's social network that is also above (below) this median, and the agent will adopt its friend's value of G if it is higher (lower) than the agent's own current value. This update procedure is motivated by the social science theories of "homophily" and "conformity". That is, people tend to associate with others who are similar (McPherson et al., 2001) and desire to have one's attitudes and behaviors conform to others in one's social network (Axelrod, 1997; Bednar and Page, 2007). Note that, over time media influences will tend to increase or decrease the median of the G values of the entire agent population as a whole, while social influences cause a slight bimodality in the evolving distribution of G.

In step 2, the agent probabilistically decides whether to consider purchasing a new vehicle during the current year, based on the age of its current vehicle and a normal probability distribution centered on the agent-specific number of years (Y) the agent expects to own each of its vehicles before purchasing a new one.

In step 3, agents willing to consider purchasing a vehicle estimate the relative costs (RC) of all vehicles being considered. First, the agents estimate the cost (C) of each vehicle by summing the purchase cost ($C_{Purchase}$), which is the sticker price less than any available rebates, the net present value of all financing costs ($C_{Financing}$) and, optionally, the estimated operating costs due to gasoline consumption ($C_{Gasoline}$) as well as electricity costs due to battery recharging ($C_{ElectricRecharge}$), if any:

$$C = C_{Purchase} + C_{Financing} + [C_{Gasoline} + C_{ElectricRecharge}] \tag{2}$$
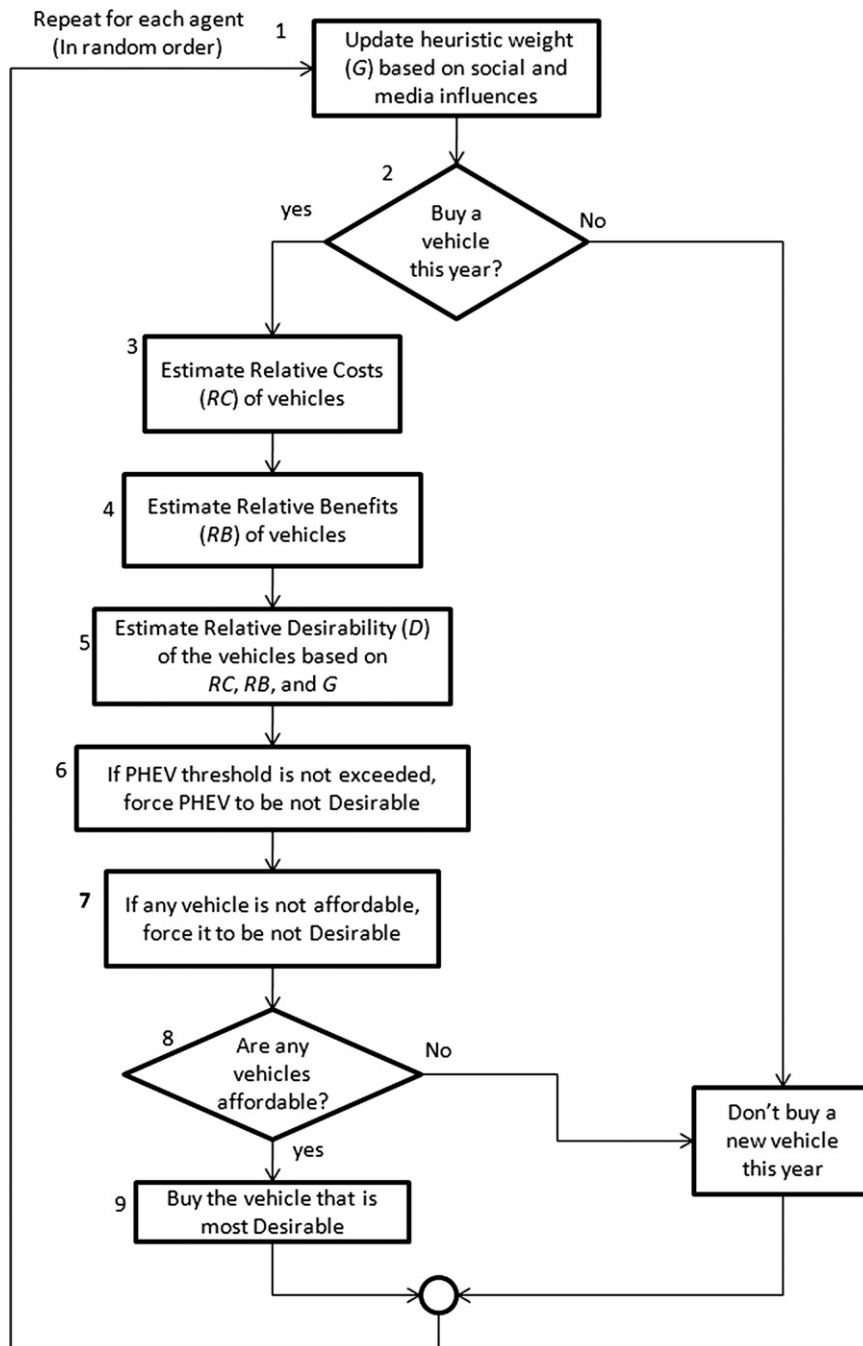
Fig. 1. Flowchart of annual agent vehicle updates. Numbered steps 1–9 are described in more detail in the text.

Agents are assumed to finance the remainder of the vehicle cost after subtracting the (depreciated) trade-in value of their current vehicle, with a four-year loan at a 6% nominal interest rate, compounded monthly. The vehicle trade-in value for a given age is estimated by depreciating its initial cost ($C_{Purchase}$) according to the following formula:

$$Trade\text{-}in = 0.93 C_{Purchase} e^{0.195 age} \tag{3}$$

Eq. (3) was determined by fitting the Kelly blue book (www.kbb.com) projected 5-year values for the 2010 Toyota Prius. This depreciation rate is assumed for all the hypothetical vehicles in this study. Maintenance costs are not currently modeled, due to insufficient information on how these might differ for PHEVs.

All agents estimate the average gasoline per mile (GPM) for each vehicle by estimating the proportion of miles they will

drive on gasoline, given the vehicle's all-electric battery range ($ElecRange$, in miles; $ElecRange=0$ for GVs and HEVs). For simplicity in this prototype implementation, we assume that the agent's daily driving distance is given by $VMT/365$ and that PHEVs are recharged once per day. Gasoline per mile is thus computed as

$$GPM = \left(1 - \min\left(\frac{ElecRange}{VMT/365}, 1\right)\right) \Big/ MPG \tag{4}$$

While purchase price and financing costs should be readily accessible to vehicle consumers, rational estimates of fuel costs require complicated calculations. Interviews with vehicle consumers indicate that most consumers do not attempt to estimate fuel costs when making vehicle-purchasing decisions that vary in fuel efficiency by a factor of 1.5, and that even the quantitatively astute consumers interviewed were not capable of rational fuel

cost estimation (Turrentine and Kurani, 2007). Nonetheless, a recent survey (Zypryme Research and Consulting, 2010) found that over half of those surveyed identified saving money on fuel as one of the top two reasons they would consider purchasing a PHEV or EV. As a result, we believe there will be increasing interest in estimating fuel cost savings for these more fuel-efficient vehicle types; we propose that if consumers were provided with a rationally calculated estimate of approximate fuel costs, they may be motivated to use this information when assessing total financial costs of vehicles (see a more complete discussion of this in Section 4). We thus model two degrees of rationality (R) in estimating projected fuel costs. Agents with $R=0$ do not make a rational estimate of projected fuel costs. Those with $R=1$ estimate gasoline and electricity costs over the agent-specific number of years (Y) they expect to own the vehicle. Specifically, each agent with $R=1$ uses an estimate of expected future average annual gasoline prices in dollars per gallon (DPG) based on a linear extrapolation from daily gas prices regressed over the year prior to the date it considers buying a vehicle. (DPG is thus a vector of length Y, which varies with the agent.) Gasoline price scenarios are stochastically generated with specified yearly, monthly, and daily variability. Each scenario is then scaled using a prescribed average growth rate to start and end at specified values; here, we report on inflation-adjusted gasoline price scenarios that rise from \$3/G (in U.S. dollars and gallons) to either \$3/G, \$6/G, \$9/G, or \$12/G (\$0.8/l, \$1.6/l, \$2.4/l, and \$3.2/l) over a 25-year time frame. These ranges are consistent with gas price projections reported in the U.S. Annual Energy Outlook (www.eia.gov). Since the model outcomes were insensitive to different specific gasoline price projections generated with the same stochastic parameters, we limited the current study to one specific set of stochastic gasoline price scenarios (Fig. 2). Total gasoline costs are thus computed as

$$C_{Gasoline} = \begin{cases} 0, & \text{if } R=0 \\ GPM \times VMT \sum_{y=1}^{Y} DPG(y), & \text{if } R=1 \end{cases} \quad (5)$$

Agents with $R=1$ also estimate PHEV recharging costs, based on the energy capacity of the PHEV battery ($BattCap$) and the nightly state of charge of the battery. For these simulations, electricity costs (EC) were initialized to \$0.11/kW h, based on average U.S. electricity pricing in 2009 dollars (www.eia.gov) and were assumed to rise linearly to \$0.18/kW h over 25 years. Since
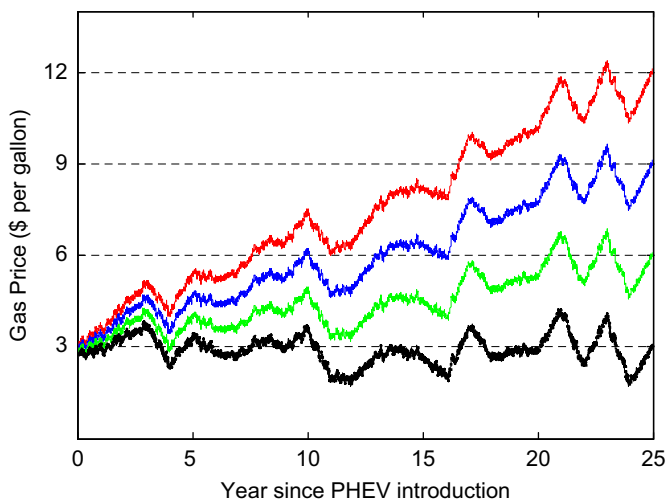

Fig. 2. Stochastically generated gasoline price projections used in the simulations reported here, where the average rate of increase is linearly scaled to end in four different final prices in year 25 (\$3, \$6, \$9, or \$12 per gallon; \$0.8, \$1.6, \$2.4, and \$3.2/l).

the results proved relatively insensitive to electricity prices, we limited the current study to this single electricity cost scenario. Total recharging costs are thus computed as

$$C_{ElectricRecharge} = \begin{cases} 0, & \text{if } R=0 \\ 365 \dfrac{\min(VMT/365, \ ElecRange)}{ElecRange} BattCap \sum_{y=1}^{Y} EC(y), & \text{if } R=1 \end{cases}$$
$$(6)$$

The perceived pair-wise relative costs (RC_{ij}) of all vehicles i and j under consideration are then estimated as

$$RC_{ij} = (C_j - C_i)/C_j \quad (7)$$

where vehicle i is the one with the lower $C_{Purchase}$.

In step 4, the agents heuristically estimate the pair-wise relative benefits (RB_{ij}) of all vehicles being considered, with respect to other concerns related to gasoline usage (i.e., other than rationally estimated financial benefits) by estimating the relative difference in gasoline usage per mile used by the two vehicles:

$$RB_{ij} = (GPM_i - GPM_j)/GPM_i \quad (8)$$

where vehicle i is again the one with lower $C_{Purchase}$. Note that agents do not consider environmental costs of electricity usage, since this is not only highly variable (by both region and time of day) but is also not generally readily accessible information to vehicle consumers.

Finally, in step 5, the agents initially compute the pair-wise relative desirability (D_{ij}) of all vehicles by weighing the relative rationally estimated costs and the relative heuristic benefits, according to the agent's current weight value G:

$$D_{ij} = G \times RB_{ij} - (1-G)RC_{ij} \quad (9)$$

If $D_{ij} \geq 0$, then vehicle j is considered to be more desirable of the two vehicles. However, values of D_{ij}, as computed by Eq. (9), can be subsequently modified, as described below.

We implement a social threshold effect, motivated by the classic works of Granovetter (1978) and Watts (2002). In step 6, the agent assesses the proportion of PHEVs owned by agents in the union of its spatial neighborhood and social network. If this proportion does not exceed the agent's personal threshold (T), then, for each vehicle j that is a PHEV, D_{ij} is overwritten with $-\infty$, thus preventing the agent from purchasing a PHEV in the current year. Individual agent thresholds are heterogeneous in our simulated populations, reflecting the varying levels of discomfort among people regarding adoption of the new PHEV technology (Curtin et al., 2009).

Similarly, if the maximum annual estimated cost of a vehicle j exceeds 20% of the agent's salary (a common rule of thumb), D_{ij} is overwritten with $-\infty$, indicating that this vehicle is not affordable (step 7). Assuming at least one vehicle is deemed affordable (step 8), in step 9 the agent assesses all pair-wise comparisons of relative vehicle desirability D_{ij} and purchases the most desirable vehicle.

2.3. Initialization of agents and their attributes

The model accounts for non-normal distributions as well as spatial and inter-attribute correlations in agent demographics that may influence vehicle selection. Initial values and distributions were based on data, where possible. For the results reported here, we simulated a 15 square mile (24.1 km²) spatial domain with randomly generated residential locations. Prior experimentation showed no qualitative differences in results from simulations with 1000 or 10,000 agents, or between different stochastic runs. Consequently, for computational efficiency we used only one run (starting from the same random seed) with 1000 agents for each unique combination of parameters in these sensitivity studies.

Two spatially correlated heat maps, with an additional correlation of $r=0.65$ between the two maps, were generated using the turning bands method (Emery, 2008), as illustrated in Fig. 3a and b. These two heat maps were then interrogated at 1000 randomly generated agent locations, concentrated into 5 hypothetical towns, and the resulting values were transformed to salary and values for the heuristic weight G, respectively (Fig. 3c and d), with bounded ranges and specified skews, using a pseudo-β transform (Eppstein et al., 1999).

In the reported simulations, annual salaries ranged from $31,764 to $201,975 with a median salary of $66,743 (Fig. 3e).

We set the lower bound on the allowable salary range to $30,000 to try to ensure that all agent salaries are generally sufficient to afford at least one of the vehicles under consideration; in all of the reported simulations, over 99% of agents always judged at least one vehicle as affordable. The heuristic weight G was initialized within the range 0–1 and, except where otherwise specified, was initially skewed to a median value of only 0.09 (Fig. 4a), based on the assumption that financial concerns are likely to strongly outweigh non-financial concerns for most buyers. We also ran simulations using (a) constant homogeneous $G=0$ and (b) constant heterogeneous G with a median G of 0.27, in order to assess model
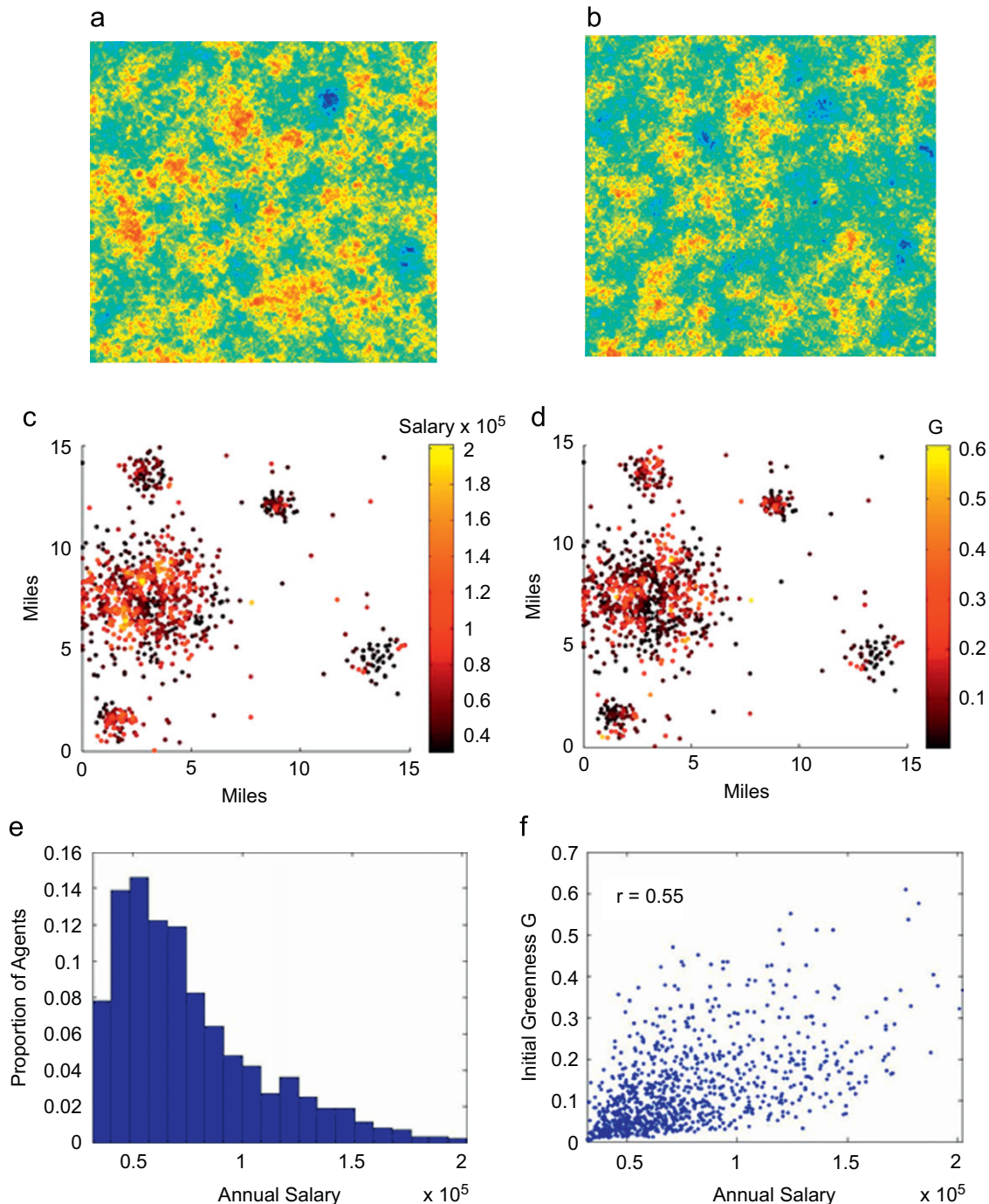

Fig. 3. Initialization of 1000 agent locations, salary, and heuristic weight G. (a and b) Two spatially and inter-correlated heat maps generated with the turning bands method, (c) spatial distribution of agents and salaries, (d) spatial distribution of initial agent heuristic weight G, (e) resulting pseudo-β distributed salaries (transformed from a), and (f) resulting cross-correlation between pseudo-β distributed salary and initial G. Salaries are in USD.

sensitivity to G. Resulting salary and heuristic weight G values are both spatially correlated (Fig. 3c and d) and loosely correlated to each other ($r=0.55$, Fig. 3f).

Salary is also used as a means of generating reasonable cross-correlations between various additional attributes. Specifically, we generated additional multivariate normal distributions that were correlated to salary and then transformed these to appropriate distributions for other variables. For example, ages of agents were modeled as pseudo-β distributed between 16 and 85 years, with a median of 39 years and a correlation of $r=0.37$ with salary. Annual VMT was created to be log-normally distributed with a median of 12,000 miles (19,312 km) (Fig. 4a) and the

number of years Y agents typically expected to own a given vehicle was initialized following a normal distribution, with a mean of 9 years and a standard deviation of 3 years, but subject to the constraint that total miles traveled by a given agent never exceeded 250,000 after Y years. The resulting distribution of Y is shown in Fig. 4b. Since both VMT and Y are generated with a correlation to salary, the result is that both are also correlated with each other (Fig. 4c, $r=-0.70$), based on our assumptions that people with higher VMT tend to buy cars more often, and agents with higher salaries have the luxury of buying cars more frequently (Fig. 4d, $r=-0.67$).

An agent's threshold (T) is the proportion of PHEVs the agent must perceive in its combined geographic neighborhood and social network (described below) to be willing to consider purchasing a PHEV. Agent thresholds are initialized to be normally distributed with a standard deviation of 0.2 and specified means. Since thresholds represent proportions, T should be bounded by 0 and 1. However, for convenience we simply interpret $T \leq 0$ as meaning the agent is willing to be an early adopter and $T \geq 1$ as meaning the agent is unwilling to consider a PHEV under any circumstances. A mean of 0 thus means that roughly half of the agents are willing to consider being early adopters. Agent thresholds, T, were also negatively correlated to salary ($r=-0.66$) based on the assumption that wealthier people feel less risk in purchasing a vehicle and therefore may have a greater tendency to be early adopters. We test the sensitivity of our model to differences in mean $T \in \{0, 0.2, 0.4\}$.

Each agent has a geographic neighborhood (Fig. 5a), comprising all other agents located within a given spatial radius of $VMT/365/16$, yielding a median spatial radius of about 2 miles (3.2 km) for the reported experiments. Each agent also has a social network (Fig. 5a), comprising all agents within its social radius, which is uniformly distributed between 0 and 5 miles (8 km), that have a similar salary ($\pm \$10,000$) and age ($\pm 5$ years). These social networks are thus constructed using the principle of homophily and provide a framework for modeling the spread of social influence within neighborhoods and socio-economic classes. This approach generates fat-tailed distributions (Fig. 5b) reminiscent of real social networks (e.g., Albert and Barabasi, 2002). An agent looks at vehicles owned by all agents in its combined geographic neighborhood and social
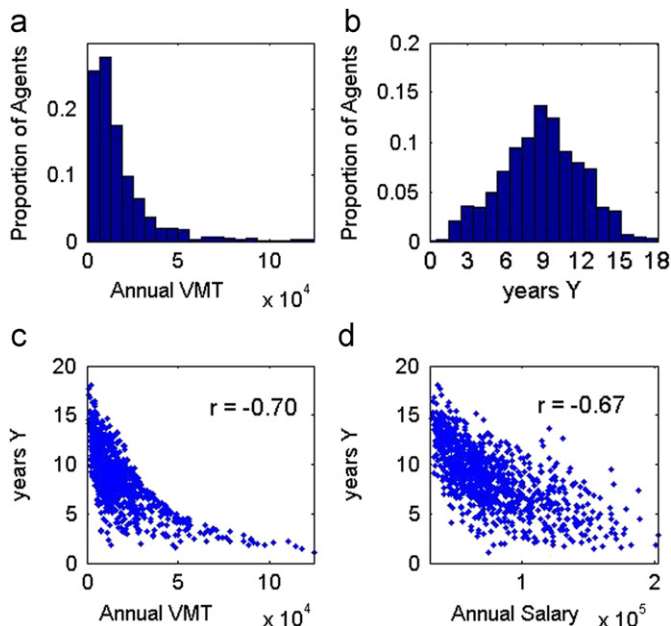

Fig. 4. Agent initializations for (a) annual Vehicle Miles Traveled (VMT), (b) number of years (Y) each agents typically own a vehicle, (c) negative correlation between VMT and Y, and (d) negative correlation between VMT and salary.
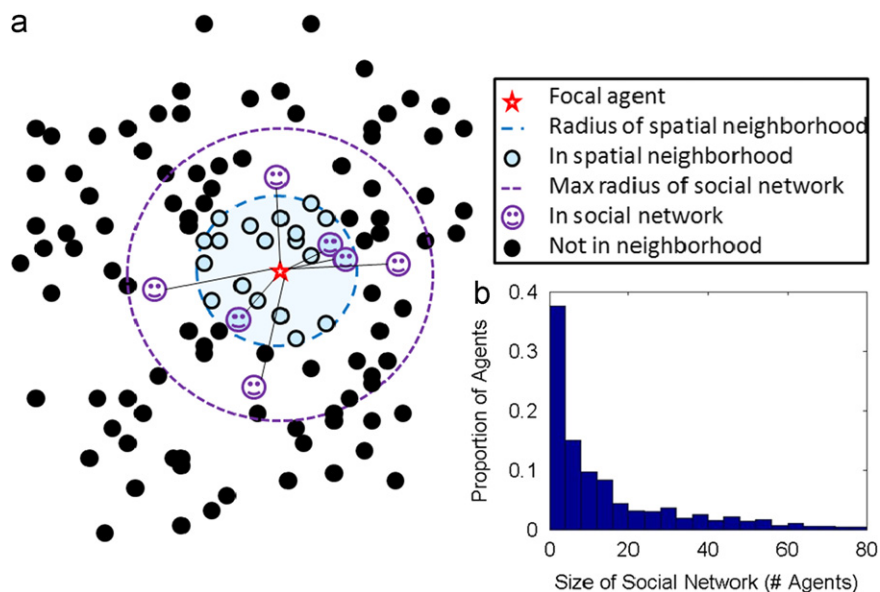

Fig. 5. (a) Agents within the spatial radius (dashed circle) are in the geographical neighborhood of the hypothetical agent marked with the star. Agents within the social radius (dotted circle) of similar age and salary are in the social network of the agent marked with a star. In the model, spatial radii are a function of each agent's annual VMT, whereas social radii are uniformly distributed; so one is not necessarily smaller than the other. (b) Frequency distribution of social network sizes for the agents in the reported simulations.

Table 1
Three vehicles available to agents in this study. Where multiple values area shown, the one in bold is the default value. NA stands for not applicable.

Vehicle type	MPG when not within all-electric range	All-electric range (*ElecRange*)	Energy capacity of PHEV battery (*BattCap*)	Sticker price	Rebate	No. of years of rebate
GV	31 mpg (13 kpl)	NA	NA	$15,000	NA	NA
HEV	50 mpg (21 kpl)	NA	NA	$25,000	NA	NA
PHEV	50 mpg (21 kpl)	One of	One of	One of	One of	One of
		20 miles (32 km)	8 kW h	$30,000	$0	0
		40 miles (64 km)	**16 kW h**	$32,500	**$7500**	**5**
		60 miles (97 km)	24 kW h	$35,000		25
				$37,500		
				$40,000		

network to assess the proportion of PHEVs for comparison to the agent's threshold *T*. However, influences on *G*, due to social conformity, are limited to an agent's social network.

Some individuals are more susceptible to social and media influences than others and most people switch attitudes or behaviors infrequently. Consequently, in this study we modeled agents' susceptibility to social and media influences (S_S and S_M, respectively) as independent pseudo-β distributed attributes, each with a strong left skew, resulting in median initial values of about 0.17. For all simulations reported here, we assumed the level of media coverage (*M*) that conveys the need to reduce gasoline, and energy consumption increases stochastically from 0.05 to 0.2 over 25 years. However, since we made the conservative assumption to have a low median S_M, the reported model results are relatively insensitive to *M*.

We initialized the fleet of agent vehicles to have a normally distributed *MPG* with a fleet average of 25 mpg ($\sim$10.6 km/l) and a standard deviation of 4 mpg, consistent with the current fuel efficiencies distribution of compact cars available in the U.S. (www.epa.gov), an average vehicle age of 5 years, and initial car prices ranging from $15,000 to $40,000 with a median of $23,000, of which we assumed 80% was initially financed.

While the model can support any number of available vehicle types, in the simulations reported here agents were allowed to select from one of the three vehicles (Table 1); a gasoline vehicle (GV), a hybrid electric vehicle (HEV), and a plug-in hybrid electric vehicle (PHEV). These three vehicles are intended to represent realistic similarly sized cars that differ largely in their fuel type, fuel efficiency, and purchase price. For example, the specifications for the GV are similar to a Chevrolet Aveo; the HEV is similar to a Toyota Prius; and the PHEV (with the default values shown in bold) is similar to those proposed for the Chevrolet Volt.

3. Experiments and results

We tested the model sensitivity to several key parameters and assumptions, and summarize many of our results in Fig. 6. The axes and surfaces are only labeled in Fig. 6a, but apply to all 6 subplots a–f. The *z*-axis in each subplot represents the total miles driven per gallon of gasoline by the entire agent fleet in the last year of a 25-year simulation, and thus implicitly accounts for the different proportions of GVs, HEVs, and PHEVs, as well as agent heterogeneity in *VMT* and portion of driving in all-electric range. The *x*-axis in each subplot represents which of the four gasoline price scenarios (from Fig. 2) were used, as denoted by the final price at the end of the simulation. The *y*-axis in each subplot indicates the proportion of agents that rationally estimated fuel costs ($R=1$), with the remainder ignoring fuel costs ($R=0$), when deciding which vehicle to purchase. The 5 different surfaces in each plot represent the 5 sticker prices tested for the PHEV (see Table 1), assuming no rebate. The simulations in Fig. 6a assume that the PHEV has an all-electric battery range of 40 miles, the

mean initial heuristic weight *G* of all agents is 0.12 (median 0.09), and a mean threshold *T* of 0 (meaning that about 50% of agents are willing to be early adopters of the PHEV). Exactly one of these parameters differs in each of Fig. 6b–f. All other variables are described in Section 2.

The fundamental nonlinear interactions between the proportion of agents that estimate relative fuel costs, gasoline price, and PHEV sticker price are illustrated in Fig. 6a. Note that if gasoline prices stay relatively low or if agents do not account for fuel costs when assessing the vehicle financial costs, the overall fuel efficiency of the fleet remains under 33 mpg, implying most of the agents own the GV (31 mpg). In these cases, results are nearly independent of the PHEV sticker price because even at the lowest PHEV price, buyers perceive the GV to be a much better buy. Only when all buyers estimate fuel costs and when gasoline prices are high does the sticker price of the PHEV vehicle have much impact on its market penetration.

In Fig. 6b the mean threshold *T* has been raised from 0 to 0.2; so the percentage of agents willing to be early adopters of the PHEV is only 16%. The response pattern is similar to that with mean $T=0$ (Fig. 6a), although there is a general reduction in the overall fleet efficiency at the end of 25 years. However, when the mean $T=0.4$ (Fig. 6c), only 2.5% of agents are willing to be early adopters and the PHEVs never achieve significant market penetration in the 25-year time frame, even when all agents rationally estimate fuel costs and gasoline prices are high. There is virtually no difference between the five surfaces in Fig. 6c, indicating that when the mean threshold is high, the PHEV sticker price becomes irrelevant.

The impact of this threshold effect is explored more fully in Fig. 7. We show selected results for simulations with the highest gasoline price scenario and where all agents rationally estimate fuel costs (i.e., this corresponds to the most sensitive region of the parameter space shown in the leftmost corners of the plots in Fig. 6). In these simulations, PHEV purchase price is $40,000, both with (thick lines) and without (thin lines) a $7500 rebate for the first 5 years. GVs (red dotted lines) comprise 28% of the market at the end of 25 years in all 3 simulations, regardless of mean *T* or whether or not there was a PHEV rebate. These factors incur a trade-off between the market shares of HEVs and PHEVs. When the mean $T=0$ (Fig. 7a), PHEVs comprise 48% of the agent fleet after 25 years; so *T* is exceeded in 99% of agents. Note that the rate of growth of the HEV market penetration continues to slow, while the growth rate of the PHEVs market penetration continues to increase as more agents have their threshold exceeded and gas prices continue to climb. When the mean $T=0.2$ (Fig. 7b), PHEVs comprise 32% of the agent fleet after 25 years; so *T* is exceeded in 72% of the agents, and the increase in PHEVs continues to climb rapidly. On the other hand, when the mean $T=0.4$ (Fig. 7c), only 2.2% of agents own PHEVs by the end of 25 years; so *T* is exceeded in only 2.9% of the agents and PHEVs cannot penetrate into the market.

The impact of the $7500 rebate for the first five years is also shown in Fig. 7a, where PHEVs are competitive with HEVs while
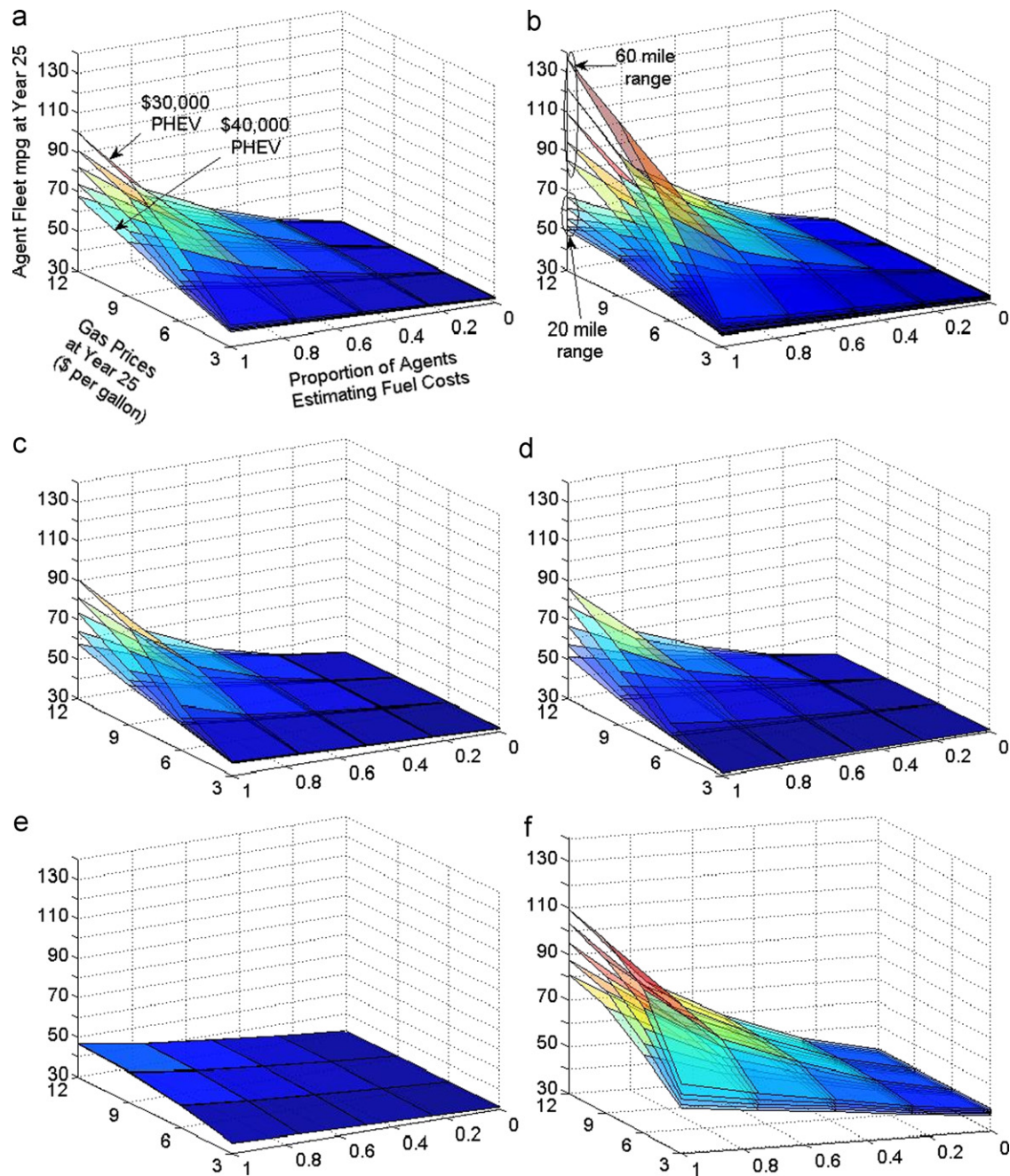
Fig. 6. (a) Model sensitivity of agent fleet mpg at year 25 (z-axis) to changes in gasoline prices (x-axis), proportion of agents with that estimate fuel costs (i.e., proportion with $R=1$; y-axis), and price of PHEV assuming no rebate (surfaces), assuming an all-electric battery range of 40 miles, initial heuristic weights G with a mean of 0.12 (median 0.09), mean threshold $T=0$ and all other variables as described in the text. Panels, b–f each, vary one parameter as compared to panel a, with all other variables being identical; (b) mean threshold $T=0.2$; (c) mean threshold $T=0.4$; (d) the lower 5 surfaces used an all-electric PHEV battery range of 20 miles, the upper 5 surfaces used a battery range of 60 miles; (e) $G=0$ for all agents and is constant throughout the simulation; and (f) G is heterogeneous but constant, with a mean of 0.32 (median 0.27).

the rebate is in force. However, the effect of the rebate is relatively short-lived; by approximately year 15, the overall PHEV market share is the same whether or not there was a PHEV rebate for the first five years. The rebate also has almost no effect at the higher thresholds (Fig. 7b and c), because in these simulations most agents are not early adopters and are therefore not willing to consider purchasing a PHEV within the first 5 years, even when the rebate is in effect. For example, with the mean $T=0.2$ case (Fig. 7b), only 20% of agents are even willing to consider buying a PHEV by the end of 5 years and gas prices have not increased enough to make the PHEV worthwhile to most of these agents.

Different manufacturers are currently developing PHEVs with different all-electric battery ranges. While most of our simulations assumed a 40-mile range (64 km, with an energy capacity of 16 kW h, as expected for the Chevrolet Volt), the impacts of changing the battery range to either 20 miles (32 km, with an energy capacity of 8 kW h) or 60 miles (97 km, with an energy capacity of 24 kW h) are shown in Fig. 6d (compare to the 40-mile range PHEV battery in Fig. 6a). Here, we see a large increase in the resulting fleet efficiency as the PHEV battery range increases. This increase in fleet efficiency occurs because 73% of the model agents have daily round-trip commutes that exceed the 20-mile battery range, as compared to 41% that exceed 40 miles,
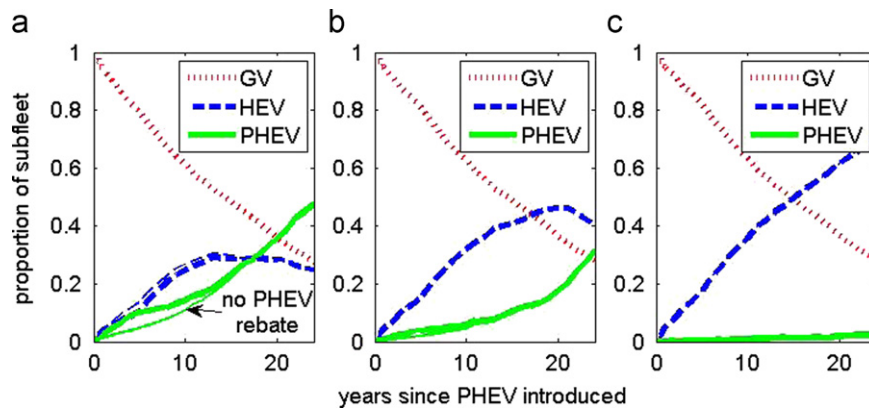
Fig. 7. Trade-off in agent selection of the HEV (dashed blue line) and the PHEV (solid green line) as the mean threshold T increases from 0 to 0.2 to 0.4 in panels a, b, and c, respectively. These simulations assumed that all agents estimate fuel costs, the price of gasoline increases from \$3/G to \$12/G over 25 years, and the price of the PHEV is \$40,000. The thick HEV and PHEV lines indicate results with a \$7500 PHEV rebate for first 5 years, whereas the corresponding thin lines had no PHEV rebate. All other variables are as described in the text. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and only 24% that exceed 60 miles. This trend has two synergistic effects on fleet efficiency. First, as the range of the PHEV battery increases, the projected lifetime fuel costs drop for more agents; therefore more agents who consider rational estimates of fuel savings purchase PHEVs, resulting in more PHEVs in the fleet. Second, the longer-range PHEVs purchased use less gasoline than shorter-range PHEVs, and therefore contribute to a higher fuel efficiency of the model fleet. In addition, there is an increasing sensitivity of fleet efficiency to PHEV purchase price at higher battery ranges. For example, when all agents consider fuel costs and gasoline prices rise to \$12 over 25 years, the difference in fleet efficiency resulting from a \$30K PHEV as compared to a \$40K PHEV is 3 times larger with the 60-mile range PHEV than with the 20-mile range PHEV.

For completeness, we controlled purchase price and battery range independently in our sensitivity studies. However, in reality these two are not independent (although the exact relationship is not yet clear as battery technology continues to evolve). However, by comparing the various surfaces in Fig. 6a and d, the combined effects of simultaneously increasing battery range and price can be explored. For example, the agent fleet efficiency surface predicted by our model for the 60-mile range battery in a \$40,000 PHEV is only slightly higher than that of the 40-mile range battery in a \$35,000 PHEV but significantly higher than that of the 20-mile range battery in a \$30,000 PHEV, indicating the potential for synergistic nonlinearity in the value-added benefits of extending battery range.

Our model assumes that different buyers weight heuristically estimated benefits differently. While we have no doubt that this fundamental assumption is valid (e.g., as supported by the findings of Heffner et al. (2007), Turrentine and Kurani (2007), Curtin et al. (2009), Griskevicius et al. (2010), and Zypryme Research and Consulting (2010)), we have little data to guide the selection of the distribution of this heuristic weighting factor. In most simulations, we make the conservative assumption that, for most buyers, financial concerns will outweigh heuristically estimated benefits; so G was initialized to be skewed far toward 0, with a mean of 0.12 and a median of 0.09 (Fig. 8a). However, to test the model sensitivity to this distribution we ran additional simulations in which $G=0$ for all agents (Fig. 6e) and G was initialized with a mean of 0.32 and a median of 0.27 (Fig. 6f) and remained constant throughout the simulation. Fig. 6e shows model results when rational financial concerns were always the deciding factor in electing to buy a GV, HEV, or PHEV. When gasoline prices are high, many agents with $R=1$ realize it is cheaper in the long-term to purchase the PHEV and the overall
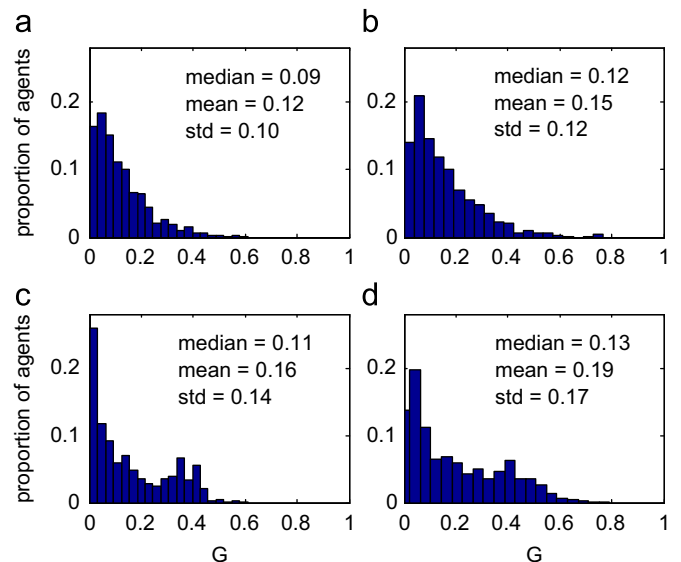

Fig. 8. Unless otherwise specified, all simulations reported started with an initial pseudo-beta distribution of heuristic weights G as shown in panel a, and had a final distribution of G as shown in panel d, after 25 years of social and media influences. Panel (b) shows what the resulting distribution would be due to 25 years of media influence alone, while panel (c) shows what the resulting distribution would be due to 25 years of social influence alone.

fuel efficiency of the fleet can be increased significantly. Not surprisingly, a higher median G (Fig. 6f) both increases the overall fleet efficiency and reduces the sensitivity of the results to gasoline prices, because more agents make their vehicle-purchasing decisions based on heuristically estimated benefits that favor more fuel-efficient vehicles, regardless of actual savings in fuel costs. This is clearly shown in Fig. 9, where an increase in mean initial G increases PHEV market share by cutting into the market share of both GVs and (to a lesser degree) HEVs.

Agent values of G can be influenced through media to which all agents are exposed (including news, public service announcements, and advertising), as well as via social interactions within agent-specific social networks. Using the methods and parameter assumptions described in Section 2, the net effect of both media influences and social interactions on the distribution of agent values of G after 25 years is shown in Fig. 8d. By turning off the social influence component of the model ($S_S=0$), the media influences due to increasing M simply shift the overall distribution to the right (Fig. 8b), since this is a global effect. Conversely,

when media influences are turned off ($S_M=0$), social influences in the model also increase the mean G but also make the population bimodal (Fig. 8c), with some agents actually adopting lower values of G.

The spatial correlations in agent attributes, and the spatially local effects of social influence and perception of fleet proportions used in assessing whether thresholds have been exceeded, translate into spatial correlations in vehicle type. In Fig. 10 we illustrate the spatial distribution in GVs, HEVs, and PHEVs for a representative run, where the heat maps were created by computing mean proportions of vehicles in 1 square mile sliding windows over the domain.

4. Discussion

We identify six primary leverage points where vehicle manufacturers and policy-makers could influence PHEV market
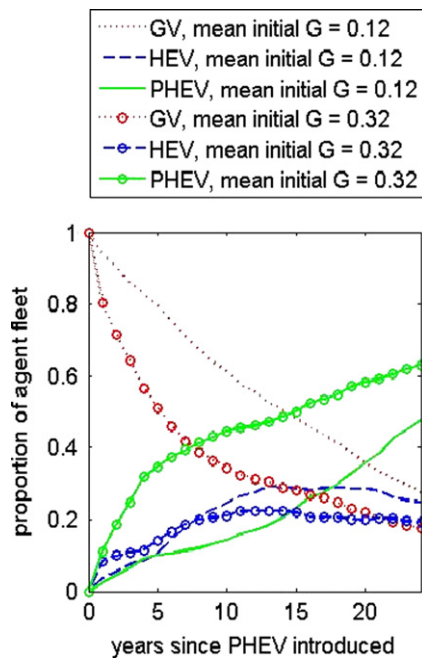

Fig. 9. Sensitivity to mean initial G. For these simulations, mean threshold $T=0$, gasoline prices rose from $3 to $12 over 25 years, PHEV price was $40,000 with a $7500 rebate for 5 years, and G was allowed to change dynamically subject to social and media influences.

penetration (Table 2), and several U.S. Federal and State Incentives and Laws already implement some forms of many of these (www.afdc.energy.gov/afdc). However, each of these potential influences has an associated cost. How should vehicle manufacturers and policy-makers prioritize investments to promote PHEV market penetration? What combinations of influences are the most effective and the most cost-effective? Here, we discuss ways that our ABM can begin to address these questions.

Understanding the cross-correlated spatial and demographic variability in consumer attributes and social and media influences on consumer attitudes may be useful to vehicle manufacturers and policy-makers at various levels of governance. However, currently available data are insufficient for accurate parameterization of the spatial and inter-attribute cross-correlations and distributions built into this model. Furthermore, our model does not currently account for the supply-side restrictions on vehicle availability or feedbacks between vehicle sales and manufacturing and this study focused only on one class of vehicles (compact cars). We also model all agents as having access to recharging facilities as needed, resulting in some over-prediction of PHEV purchases. Our choice to model individuals rather than households may also result in some over-prediction, although a recent survey reported that 78% of respondents were likely to purchase an EV or PHEV within the near future and would use it as their primary vehicle (Zypryme Research and Consulting, 2010). To some extent, the modeled threshold effect helps compensate for these over-predictions. While we cannot claim our model provides accurate quantitative predictions, it nonetheless explores potential nonlinear interactions between various influences, provides insight into the combinations of policies and procedures that may be most effective, and informs what additional data types may be most useful to gather.

While HEVs currently have higher average 5-year costs at today's North American gasoline prices than comparable GVs (BCAA, 2010), lifetime costs of the more fuel-efficient PHEVs will become lower than those of HEVs and GVs for many consumers, as gasoline prices rise and PHEV battery ranges increase. Our model results indicate that helping vehicle consumers to better assess the benefits of lifetime fuel costs may be an important factor for encouraging PHEV market penetration. Fortunately, it should be relatively inexpensive and easy to provide consumers with the means to easily estimate lifetime fuel costs for different vehicles. For example, governmental regulators (e.g., U.S. Environmental Protection Agency) could mandate that manufacturers include low/high anticipated 5-year fuel costs on the vehicle sticker. Although these would be less accurate than customized calculations, providing this information with the sticker price may make the
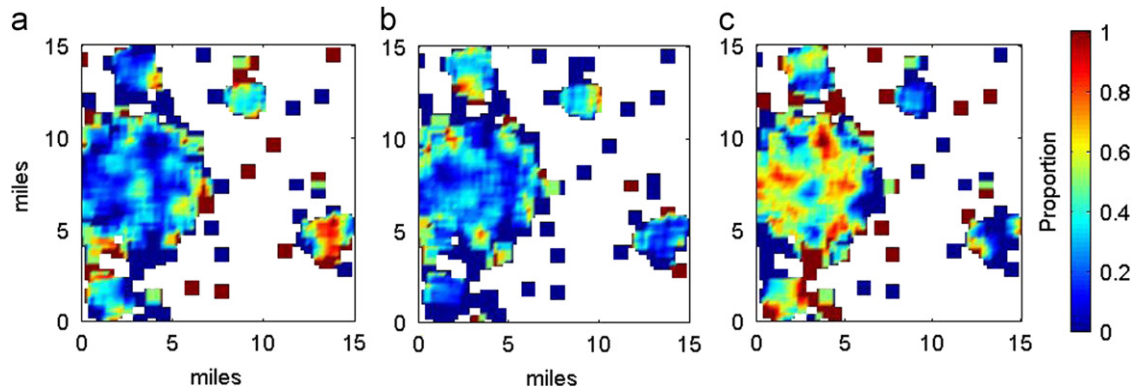

Fig. 10. Spatial distribution of (a) gasoline powered, (b) hybrid electric, and (c) plug-in hybrid electric vehicles at the end of a 25-year simulation with mean threshold $T=0$, gasoline prices rising from $3 to $12 over the 25 years, and a PHEV price of $40,000 with a $7500 rebate for 5 years. Regions shown in white had no agents in them (compared to Fig. 3c and d).

Table 2

Important factors that will affect PHEV market penetration, and some potential ways to influence them. Relevant model parameters are shown in parentheses.

Potential leverage points	Examples of potential vehicle manufacturer and dealer influences	Examples of potential governmental influences
Purchase price of PHEV ($C_{purchase}$)	Keep sticker price as low as possible to stimulate sales and get PHEVs into the market; try to lower PHEV sticker prices when rebates are retired	Rebates or tax credits to PHEV purchasers, state sales tax rates sensitive to fuel efficiency; tax breaks or other manufacturer incentives to keep PHEV sticker prices low
Gasoline price ($C_{Gasoline}$, $C_{Electricity}$)	NA	Gasoline tax; keep electricity costs low relative to gasoline price
Battery range of PHEV (GPM, $C_{purchase}$)	Prioritize research and development of long-range affordable PHEV batteries	Tax breaks or other manufacturer and research incentives battery improvements
Ability of vehicle consumers to accurately assess fuel costs for GVs, HEVs, and PHEVs (R, $C_{Gasoline}$, $C_{Electricity}$)	Provide easy-to-use fuel cost estimators on websites and on kiosks in dealerships; include bounds on 5-year fuel cost estimates on sticker, based on typical driving patterns and high and low EIA gasoline cost projections	Require vehicle manufacturers to include average estimated lifetime costs on the sticker; provide easy-to-use fuel cost estimators on websites; use PSAs to educate consumers on the magnitude of PHEV fuel savings
Comfort level of vehicle consumers in adopting the new PHEV technology (T)	Provide strong PHEV battery warranties; provide for PHEV battery trade-ins; provide PHEV battery leasing options; repurpose used PHEV batteries	Use PSAs to educate consumers; provide rebates or tax breaks for PHEVs and household electric service upgrades needed for recharging; install municipal recharging stations
Relative weight that consumers place on rational financial vs. other reasons to save gasoline (G)	Use PHEV advertisements to raise consumer awareness of environmental benefits; focus initial PHEV distributions and marketing on more environmentally minded regions	Use PSAs to educate consumers on environmental and energy security concerns; keep environmental issues visible through press conferences, policy discussions, etc.

information very psychologically "accessible" (Kahneman, 2003) and influence more fuel-efficient PHEV purchases, much as the Energy Guide labels and Energy Star® ratings have dramatically boosted the market share of energy efficient home appliances in the past decade (Dethman and Associates, 2004). For those seeking more accurate estimation, simple tools (such as web calculators or automated kiosks in dealerships) could query consumers about their typical daily VMT, percent of city driving, place of residence, and expected duration of ownership of their next vehicle. Based on this information, users could be provided with a range of expected lifetime vehicle fuel costs, using high and low governmental gas price projections, while accounting for regional differences in electricity and gasoline prices. The collected data could prove a valuable resource for vehicle manufacturers and researchers, if users waived their rights to it, providing incentive for the creation of such tools. Effective media advertising (e.g., through PSAs) may also help consumers understand the lifetime costs of different vehicle types to encourage PHEV adoption, and point to relevant website calculators. This point of leverage could have a large effect on increasing fleet efficiency at relatively low cost to policy-makers.

Consistent with the findings of Diamond (2009) and Morrow et al. (2010), our model indicates that, as long as the purchase price premium for PHEVs remains high, PHEV market penetration is not likely to increase significantly unless gasoline prices rise, which argues for a gasoline tax to at least set a floor on gas prices. Lowering the PHEV purchase price amplifies the impact of rising gasoline prices on resulting fleet efficiency.

Another potential hindrance to widespread PHEV adoption will be uncertainties associated with the new PHEV battery technology (Sovacool and Hirsh, 2009). This is reflected in our model by a threshold effect, where various agents are not willing to consider a PHEV purchase until they see enough in the fleet around them. In most simulations, we selected an average threshold such that 50% of the agents were willing to consider being early adopters of the PHEV technology. Although this is consistent with a 2009 U.S. survey (Curtin et al., 2009), which reported that nearly half of consumers would consider a PHEV if the price premium were low enough, the survey did not address the concept of threshold levels. Incentives such as PHEV purchase

rebates and gas taxes will have little effect on PHEV market penetration if consumer confidence thresholds have not been met; it is thus critical to gain a clearer understanding of consumer willingness to consider PHEVs before large investments are made in these other areas. There are certainly several potential ways to allay consumer fears regarding the uncertainties associated with PHEV batteries, some of which are already being explored. For example, strong warranties on the PHEV batteries, battery swap programs, used battery trade-ins with battery repurposing or recycling to mitigate replacement costs, PHEV battery leasing options, etc. Advertising and public service announcements (PSAs) could be used to educate consumers about these programs. Investments in public rapid recharging stations, such as that currently underway in San Francisco Bay Area in California (Borrmann, 2010) will also increase public awareness and comfort with PHEV technology. In time, resistance to this technology will likely recede.

Unless enough buyers are willing to be 'early adopters' of the PHEV technology, our model results indicate that temporary rebates on PHEV purchase are not likely to significantly impact PHEV market penetration. Even assuming approximately half of new vehicle consumers are willing to consider buying PHEVs, our results indicate that temporary rebate programs are not likely to have a lasting effect on fleet efficiency per se.

Increasing consumer appreciation of non-financial reasons to minimize gasoline usage could also increase PHEV market penetration significantly. Public opinion can be influenced through media (Yin, 1999; Newig and Hesselmann, 2004; Pew Research Center for the People and the Press, 2009), as seen with documentaries such as Al Gore's "An Inconvenient Truth", news items such as the 2010 BP Deepwater Horizon oil spill disaster in the Gulf of Mexico, and advertising of the benefits of "green" products. Policy-makers could increase media attention to the need to reduce gasoline consumption in a variety of ways (e.g., by PSAs, making news, etc.). Viral marketing approaches (e.g., using social media) may also be employed to capitalize on the spread of ideas through social networks. Because increasing the importance that consumers place on non-financial reasons to reduce gasoline reduces the sensitivity of the market to gasoline prices, this approach could help mitigate the need for high gas taxes and

rebates and we believe this may be a cost-effective strategy that policy-makers should pursue. Nonetheless, financial considerations will always play a prominent role in vehicle selection for many buyers.

Increasing the all-electric range of the PHEV battery had a strong effect on resulting agent fleet efficiency in the model, implying that tax incentives and research dollars would be wisely spent on encouraging the development of longer-range PHEV batteries. We controlled battery range and sticker price independently in these sensitivity studies, and observed that fleet efficiency is more sensitive to PHEV sticker price with longer-range PHEV batteries. Since these parameters are not independent in the real world, careful attention must be paid to the trade-off between range and price of the PHEV battery; our preliminary results indicate that the value added by longer-range batteries grows faster than linearly with an increase in higher purchase price.

Spatial correlations in vehicle-purchasing patterns are known to exist (e.g., Zypryme Research and Consulting, 2010). Our model illustrates that local processes and spatial correlations in demographics can lead to spatial clustering of vehicle-purchasing patterns, and model results can be spatially analyzed. The model could easily be extended to account for regional differences in gasoline prices, electricity prices, cleanliness of sources of electricity generation, rebates, vehicle distribution, marketing strategies, news coverage, etc. Such a model may help decision makers better understand and optimize regionally variant policies and practices to encourage a more fuel-efficient fleet. For example, one could explore the impacts of the recently proposed regional targeting and income sensitivity of tax credits (Skerlos and Winebrake, 2010), or project future regionally variant increased demands on the electric grid infrastructure that may be caused by spatially correlated patterns in PHEV ownership.

5. Summary

We have developed an agent-based model of vehicle consumers that incorporates a variety of spatial, social, and media effects. Although we do not currently have sufficiently accurate or complete input data to yield quantitatively accurate predictions, or to warrant a more complex model, the model can still be used to explore potential nonlinear interactions between various influences that will impact PHEV market penetration, provide insight into what combinations of policies and procedures may be the most effective, and inform us as to what additional data may be most useful to gather. The spatially explicit nature of our model may help policy-makers explore the combined impacts of regionally variant policies and procedures (e.g., at the city, state, regional, and federal levels) on attaining a more fuel-efficient transportation economy.

We conclude that further research is needed to determine what proportion of consumers is comfortable enough with the concept of PHEV technology to be willing to consider becoming new adopters, and how far PHEVs would have to penetrate the market to become acceptable to those currently more hesitant. This information is necessary to understand how resources should be directed toward programs that increase consumer confidence in PHEV technology vs. those that provide financial incentives for PHEV purchase.

Assuming there are sufficient potential early adopters, our model results indicate that providing consumers with readily accessible estimates of lifetime vehicle fuel costs, such as on vehicle stickers, could be very important for promoting PHEV market penetration. As vehicle consumers learn to consider the actual financial benefits of fuel savings, increasing gasoline prices (whether through market forces or a gasoline tax) could

nonlinearly magnify PHEV market penetration and resulting increases in fleet efficiency.

Another cost-effective way to influence PHEV market penetration is by influencing consumers to place more weight on non-financial considerations that encourage lower gasoline consumption when making a vehicle purchase. However, we believe there are inherent limits as to how far this alone can influence the market, because financial considerations will always continue be an important factor for many consumers.

Our results indicate that temporary incentive programs, such as the $2500–$7500 PHEV tax credit currently offered by the U.S. government (see http://www.afdc.energy.gov/afdc), are not likely to have lasting effects on long-term fuel efficiency of the fleet, unless manufacturers are able to lower sticker prices after the rebates are discontinued. Such programs will have virtually no effect if consumer discomfort with the PHEV technology is high.

Increasing PHEV battery range is another important leverage point, and longer-range batteries amplify the impacts of PHEV sticker price. Thus, synergistic effects could be achieved, for example, by imposing a gasoline tax and using the proceeds used to fund research into lower-cost, longer-range PHEV batteries.

Acknowledgment

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