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Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model

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HIGHLIGHTS

- Various policy interventions to encourage electric vehicle adoption are examined.
- An agent based model is used to simulate individual adoption decisions.
- Policies that increase the familiarity of electric vehicles are most effective.

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ABSTRACT

Heightened concern regarding climate change and energy independence has increased interest in plug-in electric vehicles as one means to address these challenges and governments at all levels have considered policy interventions to encourage their adoption. This paper develops an agent-based model that simulates the introduction of four policy scenarios aimed at promoting electric vehicle adoption in an urban community and compares them against a baseline. These scenarios include reducing vehicle purchase price via subsidies, expanding the local public charging network, increasing the number and visibility of fully battery electric vehicles (BEVs) on the roadway through government fleet purchases, and a hybrid mix of these three approaches. The results point to the effectiveness of policy options that increased awareness of BEV technology. Specifically, the hybrid policy alternative was the most successful in encouraging BEV adoption. This policy increases the visibility and familiarity of BEV technology in the community and may help counter the idea that BEVs are not a viable alternative to gasoline-powered vehicles.

1. Introduction

The concern over climate change and dependence on foreign oil has spurred policymakers to consider various solutions to the complex and intertwined environmental, energy, and transportation problems facing the United States. One notable example of this is the Obama Administration's "EV Everywhere" initiative, which has the goal of achieving one million plug-in electric vehicles on U.S. roadways and calls for substantial government investment in electric vehicle research and development, building charging infrastructure, and establishing consumer incentive programs (Johnson, 2013). This initiative, however, faces an uphill challenge due to the significant barriers that exist to the commercial-scale penetration of electric vehicles into the U.S. auto market. Indeed, electric vehicle sales in the United States have fallen below both manufacturer and governmental expectations (IEA, 2013; Chappell, 2014). Barriers to consumer adoption are particularly daunting and include the high cost and limited driving range of electric vehicles, concerns over limited and inconvenient charging infrastructure, and a general reluctance to invest in a new and uncertain technology (Carley et al., 2013; Krause et al., 2016). There are, however, a number of possible public policy options that can be used to mitigate these obstacles. This paper considers the US context and addresses the research question: how would the implementation of select public policies affect the patterns of adoption of fully battery-powered electric vehicles (BEVs) by residential urban consumers?

Individual decisions regarding whether to purchase an electric vehicle occur at a nexus of multiple influences: consumer demographic and attitudinal characteristics, travel and driving behavior, comfort and familiarity with technology, vehicle cost and

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specifications, the larger economic environment, and the local physical and infrastructure environment. Considerable uncertainty thus exists regarding the likely impact of policy interventions. To account for this complexity, this paper develops an agent-based model (ABM) that simulates the introduction of electric vehicles into a community. It explores the interactions between various policy tools implemented by the government as well as the behaviors, perceptions, and characteristics of the community's consumer-residents. ABM, also referred to as multi-agent simulation, is frequently used in social science and marketing literatures to model how the interactions between individuals and their environments may lead to large-scale social outcomes. Combining aspects of probability, complexity science, and game theory, ABM permits heterogeneity to exist between autonomous consumer agents regarding their characteristics (e.g. perceptions, responsiveness to information, demographics, etc.), and simulates how they learn and adapt to changing environments. Further, by using this method, researchers can manipulate variables in isolation or in combination and also allow for multiple, simultaneous interactions between individual- and environmental-level variables. It therefore is a particularly appropriate tool to examine electric vehicle adoption on a social scale.

The first section of this paper offers an overview of electric vehicle technology, a description of barriers to their mainstream acceptance, and a summary of the primary policies that are being considered and/or implemented to facilitate adoption. The second section reviews two theories of consumer behavior relevant to electric vehicle adoption: the diffusion of innovation and factors that motivate "pro-social" or "pro-environmental" behavior. Third, we provide an overview of ABM–its approach and objectives–along with a description of the parameters and assumptions used to develop the model employed in this paper. The final sections of the paper present a discussion of the results and implications for policy.

1.1. *Background on electric vehicle technology and policy*

Although the basic technology has existed for well over 100 years, electric vehicles are experiencing a resurgence. The term "plug-in electric vehicles" (electric vehicles) in this study refers to vehicles that plug into a specialized electric outlet to charge their batteries, as opposed to hybrid electric vehicles whose batteries recharge as a result of driving with a gasoline engine. Two main types of electric vehicles exist: The first is a battery electric vehicle (BEV), such as the Nissan Leaf, which is fueled entirely by electricity. The second is a "plug-in hybrid electric vehicle" (PHEV), which has a back-up gasoline engine that powers the vehicle when the electric charge is depleted. In the United States, the Chevrolet Volt is the best-known example of a PHEV. A total of 15 electric vehicle models are on the market, including at least one from nearly every major automaker (Shahan, 2014). As of mid-2015, approximately 330,000 electric vehicles have been sold in the United States, accounting for about 0.67% of the new vehicle market (ETDA, 2015; Plug-in America, 2015) and approximately 1.3% of all passenger cars[1] sold (Mock and Yang, 2014).

Although a technology breakthrough may considerably increase their adoption potential (Krause et al., 2016), in its absence, electric vehicle penetration is expected to remain under 1.5% of the new vehicle market by 2020 (NADA 2013). Although the first wave of electric vehicles has been purchased quickly by a small group of niche consumers, considerable barriers to this transition exist for mainstream car buyers (Carley et al., 2013). Barriers to widespread electric vehicle adoption include their high purchase price, limited driving range on a single charge, and charging inconvenience. Electric cars are considerably more expensive than otherwise similar gasoline-powered vehicles. For example, the suggested retail prices of the Chevrolet Volt and Nissan Leaf were $15,000 to $20,000 higher than comparable gasoline-powered vehicles (NADA, 2013). Even with the current federal tax credit, which can be up to $7500, a large price premium remains. Level-2 (240-volt) home charging stations, which can provide a full vehicle charge in three to eight hours, can cost an additional $1000 to $2000 to install (NRC, 2015). Given these additional expenses, it is no surprise that purchase price is consistently described as the most significant barrier to electric vehicle adoption (Dagsvik et al., 2002; Deloitte, 2010).

Another obstacle associated with electric vehicles, particularly in the US context, is "range anxiety." In good driving conditions, BEVs can travel between 75 and 100 miles on a full electric charge. PHEVs have a shorter electric range, but they switch to a back-up gasoline engine when the electric charge is depleted, enabling them to travel as far as a standard gasoline-powered vehicle. Although 78% of US drivers travel under 40 miles a day (U.S. DOT, 2003), the fear of running out of electric charge and becoming "stuck" somewhere is a significant concern to potential consumers (Deloitte, 2010; Synovate, 2010). Range anxiety may be particularly large for households with only one car. Because of their range limitation, BEVs face an additional obstacle to adoption that is not relevant for PHEVs.

The length of time it takes to charge an electric vehicle and the limited availability of public chargers relates directly to range anxiety. Depending on the type of charger, it can take between four and 20 h to charge a vehicle completely. Although chargers do exist that can charge a battery in 30 min, they are quite expensive and their availability is limited. Most charging will likely occur at people's homes or workplaces, but the lack of public chargers in many communities is another concern and contributes to range anxiety (Synovate, 2010).

Electric vehicles, and eco-innovations in general, are often recognized as warranting supportive governmental intervention because of the negative externalities they help to mitigate as well as the positive externalities they produce (Graham et al., 2011). Conventional vehicles, with their gasoline combustion engines, generate negative externalities in the form of greenhouse gas emissions, air pollution, and energy insecurity. Although, if fossil fuel based, the electricity used to power electric vehicles yields similar types of negative externalities, the mile-for-mile magnitude of the negative effects is considerably less. This remains true even in locations where electricity generation is dominated by coal (Anair and Mahmassani, 2012; Nigro and Jiang, 2013). Moreover, positive externalities may result from electric vehicle research and development, particularly in battery technology improvements, which may "spill over" into broader society. These and similar externalities incentivize private underinvestment for many eco-innovations.

As part of the 2009 American Recovery and Reinvestment Act, $2.5 billion was allocated to subsidize battery manufacturing projects, vehicle component production, construction of production facilities, and demonstration projects (U.S. DOE, 2011). This allocation is on top of the $9.1 billion in loan guarantees from the Department of Energy in 2005 to support green automotive technologies more generally. The demand side of the market has also been stimulated by tax credits, rebates, HOV lane access, and a variety of other incentives provided by federal, state, and local governments and utilities (IEA, 2013). Over the last several years, the governments of virtually all the world's developed countries and China have provided incentives to encourage the production, purchase, and use of electric vehicles (Lane et al., 2013).

[1] This designation excludes "light trucks" like vans, sport utility vehicles, and pickup trucks.

Policies that target consumer behavior are particularly relevant to the focus of this paper. Initiatives similar to those currently being considered and implemented to promote electric vehicle adoption have been used previously to encourage the purchase of hybrid vehicles. Their experience therefore offers initial insights into the likely impact of some common policies. Policies that reduce vehicle purchase price consistently have been found to increase hybrid sales (Chandraa et al., 2010; Gallagher and Muehlegger, 2011). However, the delivery mechanism of the incentive appears to have considerable influence on impact, with sales tax waivers showing a dollar-for-dollar impact that is ten-times greater than income tax credits (Gallagher and Muehlegger, 2011). Nonfinancial incentives, such as HOV lane access and free parking, have typically not been found to have a significant impact on the purchase of hybrid vehicles (Potoglou and Kanaroglou, 2007; Gallagher and Muehlegger, 2011).

1.2. Relevant theories of consumer behavior

To examine the transition away from a standard technology to a new, cleaner technology that provides the same functional service, researchers must look beyond traditional economic theory and its focus on maximizing individual utility. Clean technology innovations frequently face two sets of barriers to adoption: those associated with "newness" and those associated with public goods. Because modern electric vehicles are a new and relatively unfamiliar technology, their adoption requires the acceptance of some uncertainty and risk. Further, unlike many innovative products (like smartphone technology, whose benefits are exclusive to the adopting consumer), the value of switching from a conventional to an electric vehicle is primarily social in nature. As such, two sets of theories related to consumer behavior are relevant for understanding electric vehicle adoption: the diffusion of innovations and motivations for "pro-social" or pro-environmental behaviors (Coad et al., 2009).

1.2.1. Diffusion of innovations and electric vehicles

Rogers (2003) describes diffusion as a process in which an innovation (i.e. a new idea, practice, or technology) is communicated through certain channels in a social system over time. Characteristics of each particular innovation influence its rate and the eventual extent of its adoption, whereas the characteristics of individuals influence if and when each person is likely to adopt. Numerous studies considering a wide range of technologies have found that five features of innovations generally explain between 49% and 87% of the observed variation in rates of adoption (Rogers, 2003). The first and most influential characteristic is the relative advantage that an innovation offers over the idea or product that it is intended to replace; economic benefits and increased status are the primary ways that relative advantage is conferred. Second is the innovation's compatibility with existing values, experiences, and needs. Third is the innovation's complexity or ease of understanding and use. Fourth is the ability to try out an innovation on a limited basis before making a firm commitment to adopt; a trial period helps dispel uncertainty and is particularly important for early adopters. The final attribute is the innovation's visibility to others. The rate and extent of an innovation's adoption are positively correlated with its relative advantage, compatibility, trialability, and visibility and negatively correlated with its complexity.

Based on an evaluation of their likely performance on these five attributes, the widespread and timely adoption of electric vehicles faces an uphill challenge. Although electric vehicles offer a significant relative advantage over conventional vehicles in terms of reduced urban air pollution and greenhouse gas (GHG) emissions, much of it does not accrue to the individual adopter. From a self-interested standpoint, the primary relative advantage of electric vehicles over gasoline vehicles is their lower operating cost. However, higher upfront costs mean that several years and consistently high gas prices are necessary for the individual to recoup their investment. The personal satisfaction and status that may be conferred to electric vehicle owners, particularly in "green" communities, is a secondary private advantage. As with relative advantage, electric vehicles also struggle with compatibility. Their limited battery range is inconsistent with many drivers' perceived mobility needs as well as with the individualistic and "open road" mentality held in much of the United States. The third attribute, complexity, will not likely pose a significant barrier to adoption since most people are familiar with personal vehicles and a wide variety of electronics. The "trialability" of electric vehicles is largely limited to standard test drives. Policies have been discussed that increase trialability by, for example, allowing potential buyers a one-month trial period (NYC, 2010); however, these policies have not been implemented on any large scale. Finally, electric vehicles have moderate visibility–while they are easy to see, they may prove difficult for the average person to recognize. In sum, electric vehicles fare poorly with regard to the relative private advantages they offer to potential drivers and are incompatible with some influential values on mobility. These attributes will present the biggest challenge to diffusion, whereas the latter three will likely have less of an effect. Furthermore, different "types" of individuals are more or less inclined to adopt innovations. Rogers (2003) points to socioeconomic characteristics, personality traits, and communication patterns as key determinants of people's relative "innovativeness." Rogers (2003) segmented the market of adopters into categories, based on when they began using an innovation: innovators (typically the first 2.5% of adopters), early adopters (the next 13.5%), early majority (34%), late majority (34%), and laggards (16%). A small portion of the population, innovators, act as the "gate keepers" to innovation and play an essential role in its eventual diffusion. These innovators tend to be of high socioeconomic status, to have positive attitudes towards science, to cope well with change and uncertainty, and to have broad and varied channels of social communication. At the other end of the scale, laggards generally do not adopt a new technology until it becomes an economic or social necessity. The "ambient levels of penetration" would need to be progressively higher for each of these groups to adopt; in other words, individuals in each group would need to see respectively larger numbers of electric vehicles on the roadway in order for buying one to become a reasonable option (Sullivan et al., 2009). The differences in their socioeconomic, personality, and communication characteristics suggest that the motivations and public policies able to persuade innovators to adopt electric vehicles are likely different from those policies needed to get the masses in the early and late majority to adopt.

1.2.2. Prosocial behavior and electric vehicles

Although the innovation dynamic described above is applicable to a wide variety of innovations, it was developed largely around those that provide private benefits to potential adopters. However, the primary benefits provided by switching from standard gasoline vehicles to electric vehicles–decreasing oil dependency, urban pollution, and greenhouse gas emissions–are public in nature. Therefore, purchasing an electric vehicle is an example of a "pro-social" behavior that likely would not be taken under the narrow motivation of personal self-interest. An additional layer of consideration is needed to explore the adoption of innovations that primarily advance the public good.

Three broad categories have been identified in the literature as drivers of pro-social behavior: intrinsic, extrinsic, and image motivations (Ariely et al., 2009). Intrinsic motivations are based on a personal preference for contributing to the social good. They can be driven by an altruistic concern for others, by the "warm glow" that engaging in pro-social behavior provides the doer, or by a need to support a positive self-identity (Frey, 1999; Meier, 2007). Extrinsic motivation, on the other hand, is an extension of the self-interest model and involves material rewards or benefits received for engaging in pro-social behavior. Extrinsic incentives decrease the relative cost of engaging in pro-social acts and can come in a variety of forms, including tax credits, rebates, and additional conveniences. The third type of motivation is based on social imaging or signaling. People generally seek social approval and are concerned about how others perceive them. They therefore make a conscious effort to display traits considered "good" by their reference group. Engaging in pro-social or altruistic behavior sends the signal that an individual is generous or thoughtful–traits generally considered good–and helps create that individual's positive social image. Visibility is a key component of imaging, and if others cannot see an individual's good behavior, the motivation loses its influence. As such, people tend to act more pro-socially in public than they do in private (Ariely et al., 2009). These three types of motivations interact with each other as well as with personal and demographic characteristics. Depending on whether people are innovators, early adopters, late adopters, or laggards, different types and quantities of motivation are needed for them to choose to purchase an electric vehicle.

1.3. Agent-based modeling

This paper explores the diffusion of a subset of electric vehicles, battery electric vehicles (BEVs), and the impact that different public policies have on their adoption. We developed an ABM that simulates the introduction of BEVs into a new community. We focus specifically on the adoption of BEVs because that vehicle technology has the greatest potential to achieve the previously discussed social benefits of increased energy independence and emissions reductions. They also face the most significant barriers to adoption. ABMs are built upon the repeated interactions of autonomous and heterogeneous entities, or *agents*, each making decisions according to a specific set of stated rules. These agents differ from each other in important characteristics, including their attitudes toward technology and the environment, responsiveness to information, and demographics. Agents are driven by goals, can be influenced by each other, learn from their environment, and adapt to changing circumstances and new information. The central role that the interactions between agents and their environments plays in ABM is what differentiates it from other systemic modeling approaches and makes it a particularly appropriate methodology to assess the likely effects of different policy scenarios (McLane et al., 2011).

Because agents act as the individual building blocks of ABMs, group behavior is simulated from the bottom up. As such, ABM has been described as "growing" social behavior (Epstein and Axtell, 1996). This approach is particularly useful for modeling the diffusion of innovations and other "emergent phenomena" which, because of interactions, cannot be reduced to the sum of its parts or for which there is insufficient empirical data (Bonabeau, 2002). Moreover, ABM enables the creation of a controlled experimental environment in which one treatment can be altered at a time, allowing changes in outcome to be directly attributed to that treatment (Gilbert, 2008). In recent years, agent based simulations have been used as part of policy experiments aimed at predicting the *ex-ante* impact of public policy interventions in the fields of agriculture and land use (Schreinemachers and Berger, 2011), public health (Auchincloss et al., 2011; Yang et al., 2011; Kumar et al., 2013) and household energy use (Sopha et al., 2011).

Agent-based models can range from abstract theory development models to facsimile models that aim to predict outcomes in specific contexts. Facsimile models utilize "real-world" environments, often imported from geographic information systems, and correspond to actual topography. Artificial environments provide simplified representations of context and are commonly used when the focus is on behavioral rules rather than the dynamics of a particular ecosystem (McLane et al., 2011). Like others aimed at assessing the effect of policy interventions (e.g. Sopha et al., 2011), the model developed in this paper utilizes a middle range simulation that describes the characteristics of a particular phenomenon but does not intend to replicate any single situation or locale. The outcomes of successful middle range simulations qualitatively resemble reality; however, they do not provide a firm foundation for quantitative forecasts (Gilbert, 2008). Moreover, as with all empirical models, the quality of ABM results is tied directly to their inputs, in this case parameter assumptions, environmental set-up, and the information on which both are based.

1.4. Electric vehicle ABM design

A handful of studies have used ABM to model aspects of electric vehicle diffusion (e.g. Brown, 2013; Shafiei et al., 2012; Sweda and Klabjan, 2011). Of these studies, most have focused on simulating vehicle markets to estimate the market share that electric vehicles are likely to have under different price and technology contexts. Findings from these studies reflect the varied scenarios examined and range from electric vehicles making up less than 1% of new vehicle sales by 2020 (Zhang et al., 2011) to achieving full market share by 2030 (Shafiei et al., 2012).

The model in this paper takes a somewhat different approach. Rather than simulating an electric vehicle marketplace where consumers, governments, and manufacturers interact, the model in this paper focuses on consumer behavior and simulates how that behavior is likely to change in response to public policies. As such, consumers' socioeconomic characteristics, travel behaviors, and environmental attitudes are key factors that interact with vehicle and policy attributes to influence purchase decisions. This enables us to gain insights into the total market share that may be achieved with various policy interventions. This approach also provides insights into the demographic profiles of those who are inclined to adopt electric vehicles under different policy scenarios, providing the information necessary to develop better, more targeted policies.

1.5. Simulation environment

This paper addresses the following research question: how would the implementation of select public policies affect the patterns of adoption of fully battery-powered electric vehicles (BEVs) by residential, urban consumers? The specific policy interventions examined here include publically subsidized reductions to the BEV purchase price, the construction of a public charging network, and the purchase of BEVs as part of government vehicle fleets to increase public awareness of and familiarity with electric vehicle technology as individuals see more BEVs on the roadways. These reflect some of the most common types of consumer-focused policies employed within cities and states in the United States as well as by other countries around the world (Lane et al., 2013; Sierzchula, 2014).

The parameters of the current simulation are grounded in empirical data and probability distributions. The simulation is structured in an environment that represents a generic urban roadway network containing 250,000 cars. Assuming the U. S. average of .841 cars per person, this is equivalent of a metropolitan area of approximate 300,000 people (U.S. DOE, 2010). The model is scaled at a ratio of 1:100, so 2500 cars will represent the full 250,000. NetLogo 5.0.5 was used to run the ABM simulations.

The simulation environment is divided into four distinct geographic sections that represent areas in a hypothetical city: a downtown/business district and upper-, middle-, and lower-income areas (see Fig. 1). Electric vehicle charging stations are a second component of the simulated environment. The total number of charging stations that are present in the environment is a product of the policy scenario being modeled. In some scenarios, there are no public chargers. When chargers are present, their exact locations change randomly between each run, pursuant to parameters specifying that 50% of the charging stations will be placed in the business district, 25% in the upper-income areas, 25% in the middle-income areas, and none in the low-income areas. This ensures that, although randomized, the charging network will not deviate significantly from the structures in most cities where public electric chargers are located in downtown business districts or in upscale residential or commercial areas.

1.6. Agents and parameters

This simulation includes two primary types of agents: initial BEV drivers and non-BEV drivers. Each agent is characterized by a number of attributes relevant to automobile purchase decisions. Attributes are randomly assigned to each agent but follow pre-determined distributions and/or are based on actual known parameters. Table 1 describes the various attributes assigned to each BEV and non-BEV agent. As agents move around the simulation environment, they are aware of their immediate surroundings and can be influenced by the actions of other agents and their environment. When agents pass in direct proximity to charging stations or BEVs in the model, they are programmed to recognize or “see” this new technology. To mimic actual driving habits, agents are programmed to look around at their environment each time they pause – such as at a corner or red light – along their journey through the city.

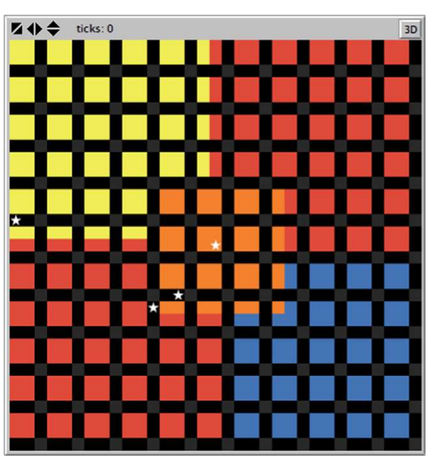
The initial number of BEV agents is determined exogenously as part of the policy scenario being modeled. The initial BEV agents are taken as a given and are characterized by a simpler set of attributes than the non-BEV agents, which are faced with the decision of adopting a BEV or not. A key characteristic of the non-BEV agents is their income level. Agents' income is based on U. S. census data and follows a probabilistic gamma distribution (U.S. Census Bureau, 2009). Income is used to determine each agent's “home location” in the simulated environment. Most agents will be placed in the neighborhood that corresponds to their income level (i.e. wealthy agents are most likely to be placed in the wealthy neighborhood). However, to allow for heterogeneity and to be more representative of many actual communities, the economic segregation is not strict and some portion of lower income agents are placed in wealthier neighborhoods and vice versa (see Table 1). The impact of socioeconomic integration on BEV adoption is examined further in the model sensitivity analysis portion of the paper. The “home location” of initial BEV agents is randomly determined, but as with the charging stations, their location is pursuant to parameters specifying that half be initially placed in the business district, with the remaining agents being placed in either upper- (40%) or middle-income areas (10%).

2. Decision rule

This paper simulates the decision-making structure of individuals regarding electric vehicle purchases. Although commercial vehicle fleets and/or government purchases may comprise a significant portion of the initial electric vehicles bought, these adoption decisions are not explicitly modeled. Commercial and/or government-owned BEVs are instead included in the initial number of BEVs on the roadway, which can be adjusted to reflect different policy scenarios. In the initial run of this model, we assume that 0.08% of all cars on the road are BEVs. This represents a higher proportion than that which exists currently in the United States as a whole, but it is reasonable for many urban communities. For comparison, San Francisco has the highest percentage of electric vehicles on U. S. urban roadways. There, 0.52% of all registered vehicles in the city are electric (Gorzelany, 2013).

Individual consumer agents in the model follow the decision rules depicted in Fig. 2. Eight main questions are involved: (A) Is the agent in the market to purchase a vehicle? (B) Can the agent afford to purchase an electric vehicle? (C) Does a BEV fit the agent's driving habits in terms of having a range longer than their average daily commute? (D) Does the household have another means available to make less frequent but necessary longer trips (e.g. a second car)? (E) Is a BEV a cost effective alternative to a gasoline-powered vehicle? (F) Does the agent place a high value on the environment? (G) Is the agent an innovator? (H) Is the agent sufficiently familiar with BEV technology, through seeing enough BEVs and charging infrastructure in the community, to be comfortable purchasing a BEV?

A BEV may only be adopted when the age of an agent's current vehicle exceeds the vehicle age at which the agent seeks to replace that vehicle (question A in Fig. 2). On average, agents purchase a new car every 72 months (6 years), based on a normal curve with a standard deviation of 24 months. At the point when the agent is ready to purchase a new car, he or she can choose to buy a BEV or a gasoline-powered vehicle. This choice is dependent upon answers to the remaining seven questions in the decision logic.



Downtown business district – Orange

Wealthy residential/commercial – Yellow

Middle-income residential/commercial – Red

Lower-income residential/commercial – Blue

Electric vehicle charging stations – Stars

Fig. 1. Example simulation environment.

Table 1.
Explanation of the attributes of simulation agents.

Agent 1: Non-BEV driver	
Attribute	*Explanation and source*
Income	Household income in the U.S. has a mean of $67,465, a standard deviation of $66,700, and follows a gamma distribution. Incomes are assigned to agents accordingly[a].
Home location	Based on their household incomes, drivers are assigned to a "home location" in either the central business district or an upper, middle, or lower socioeconomic area. Home location influences drivers' exposure to BEVs and charging stations. In the model presented in this paper the home location of all low-income drivers was set to the low income area of the city. For the middle-income drivers, 70% of them were assigned to reside in the middle class neighborhoods, 20% were assigned to the upper-income area, and the remaining 10% were assigned to live in the low income area. Finally, 80%, of upper income drivers were assigned to the upper-income area of the city with the remaining 20% assignment to the middle-income areas of the city. *(Varied in sensitivity analysis)*
Driving route / daily miles traveled / need for longer-range vehicle	Drivers travel such that they always leave from and return to the same "home location." Each driver will drive a route that is randomly determined for each round of the simulation. Each car also has an average trip length that is assigned randomly. Trip distances for all vehicles follow a random normal distribution with a mean of 32 miles, which reflects average vehicle miles traveled in the U.S.[b]. Regardless of their average daily mileage, 10% of agents are randomly assigned as requiring access to a conventional vehicle to make occasional longer trips.
Vehicle age	The age of each driver's car is determined by randomly assigning values that follow a standard normal distribution with a mean of 60 months (five years) and a standard deviation of 20 months. Car age increases during each round of the simulation. If a new car is purchased, the vehicle age is reset to zero.
Purchase age	The age at which a new car is purchased. Randomly generated with a mean of 72 months (six years) and a standard deviation of 24 months.
Purchase price threshold	Agents are allowed to spend up to 11% of their gross annual household income on a new car purchase. The average American spends 11% of their gross monthly income on a car payment[c]. *(Varied in sensitivity analysis)*
Innovativeness	Each driver is randomly and independently assigned scores indicating their innovativeness. The scores are normally distributed with a mean of 3 and a standard deviation of 1. Conforming to Rogers (2003), agents are divided into innovation categories based on where their scores fall relative to the rest of the population:

Innovativeness class	***Innovativeness score***	***Percent of population***
Innovator	Score ≤ 1	$\approx 2.5\%$
Early Adopter	$1 <$ Score ≤ 2	$\approx 13.5\%$
Early Majority	$2 <$ Score ≤ 3	$\approx 34\%$
Late Majority	$3 <$ Score ≤ 4	$\approx 34\%$
Laggard	Score > 4	$\approx 16\%$

Environmental attitude	Each driver is randomly and independently assigned scores indicating their environmental attitudes. These scores are normally distributed scores with a mean of 3 and a standard deviation of 1. The 16% of agents with the highest environmental scores are classified as environmentalists[d]. The remaining 84% of agents whose normally distributed environmental attitude scores are not in this top percentile are simply classified as "not environmentalists".
Agent 2: BEV driver	
Attribute	*Explanation and source*
Home location	Based on their household incomes, drivers are randomly assigned to a "home location" in the simulation environment. Initially, 90% of BEVs are placed in the central business district or upper-income areas. *(Varied in sensitivity analysis)*

Table 1. (*continued*)

Agent 1: Non-BEV driver	
Regular driving route and length	BEV drivers travel such that they always leave from and return to the same "home location." Each BEV will drive a route that is randomly determined for each round of the simulation. Trip distances cannot exceed the maximum driving range of a BEV.

[a] U.S. Census Bureau, 2009,
[b] U.S. DOT, 2009,
[c] Sahadi, 2003,
[d] Carley et al., 2013a

Questions B–D in Fig. 2 address two major barriers to electric vehicle adoption–their high purchase price and limited driving range–and acts as basic criteria for the ability of a BEV to meet an agent's functional needs. Can the agent afford the cost of purchasing a new electric vehicle? If so, is a BEV compatible with his or her driving patterns and transportation needs? Table 2 describes the assumptions and calculations used to generate each agent's answers to these questions. Only if an agent "passes" questions A through D, can he or she be characterized as a "potential BEV adopter."

"Potential BEV adopters" are those agents in the model who are classified as being able to adopt. However, being classified as a "potential BEV adopter" does not necessarily mean that they will adopt a BEV. Additional motivation is needed for individuals to purchase a BEV. The bottom half of Fig. 2, beginning with question E, addresses these motivations. First, if BEVs are cost effective (i.e. they provide financial savings over conventional vehicles), a portion of the potential adopters will adopt. Cost effectiveness is calculated by comparing the purchase price and operating cost of a BEV with the purchase price and operating cost of a conventional vehicle over the length of an agent's vehicle ownership. When the savings achieved from lower operating costs over the ownership life of the vehicle compensate for the premium in BEV purchase price, 42% of potential adopters will adopt (Graham et al., 2011). The cost-effective calculation is explained in further detail in Table 2.

An agent may still choose to purchase a BEV as a result of other intrinsic motivations. Environmentalists and individuals who place a high value on being at the cutting edge of technology are often seen as comprising the niche group willing to purchase electric vehicles, even if doing so is not "rational" from a pure cost perspective (Carley et al., 2013). Each agent has a randomly assigned environmental attitude score and innovation score. Survey data suggests that 16% of individuals in the United States hold strong environmental attitudes (Carley et al., 2013) and will purchase a BEV (see Table 2.f).

Individuals who are not motivated by environmental concerns may instead choose to adopt a BEV based on their affinity for technology. According to their placement along a normal distribution of "innovativeness," each agent is designated as belonging to one of Rogers' (2003) five innovation adoption categories. Some agents are motivated by a personal desire to be at the forefront of technological progress. Rogers refers to this group as innovators and they are the 2.5% of a population that first adopts a technology. The agents in the other four categories, which comprise 97.5% of agents in the city, will not consider a BEV until they have encountered a threshold number of BEVs and charging stations. Technology exposure and agents' own levels of "innovativeness" interact to push towards or away from BEV adoption. Consumers must be sufficiently aware of and familiar with a technology before purchasing it; although individual considerations of what is "sufficient" vary according to Roger's distribution.

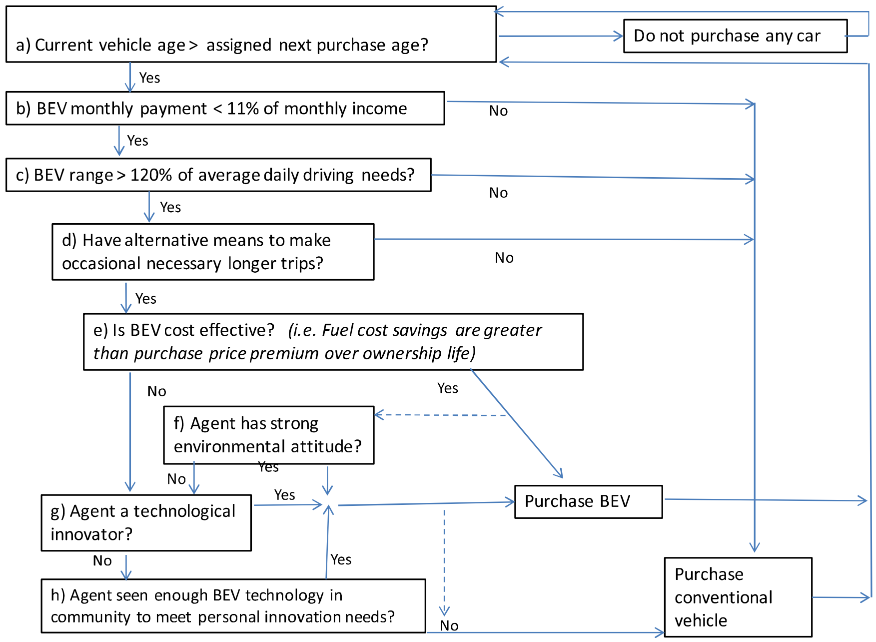


Fig. 2. Simulated decision process for vehicle purchase.

In this model, agents become aware of BEV technology by passing charging stations and driving in proximity to other BEVs. When enough have been seen to satisfy their technology comfort needs associated with their previously assigned individual innovation characteristics, the agent becomes a potential adopter. Table 2f and g contain further details regarding the thresholds for each of the innovation adoption categories.

2.1. *Scenarios and potential policy interventions*

This paper uses several policy intervention scenarios to demonstrate the likely effect that adjusting vehicle purchase price via subsidies, expanding the local public charging network, and/or increasing the number and visibility of BEVs on the roadway through government fleet purchases will have on consumer adoption.

The baseline scenario employs the following initial assumptions: BEVs cost $35,000 to purchase, $4.00 to fully charge, and have a 100-mile range per charge. Home charging equipment, which accompanies the purchase of a vehicle, costs an additional $2000 to install. Agents are willing to spend up to 11% of their monthly gross household income on a car payment. Gasoline is $3.50 per gallon.[2] Otherwise comparable combustion engine vehicles get 25 miles per gallon (MPG) and cost $20,000 to purchase. Additionally, 10% of drivers whose average driving distance is less than 100 miles need a vehicle that can exceed that for longer trips. This equates to approximately 30% of all people in one-car households in the United States (U.S. Census Bureau, 2009).

The policy intervention scenarios assume that the modeled community has $5.5 million available to promote BEV use within its jurisdiction. This reflects the average amount of funding that cities with populations between 250,000 and 350,000 received for energy and environmental projects from the 2009 American Recovery and Reinvestment Act (recovery.gov, 2012).[3] Within these parameters, the impacts of the following five policy options are simulated:

1. *Baseline scenario:* No policy intervention;
2. *Incentive scenario*: Provides 550 subsidies worth $10,000 each, thereby reducing the purchase price of this number of BEVs;[4]
3. *Electric charger scenario:* Installs 350 electric charging stations at various locations in the city;[5]
4. *City fleet scenario:* Purchases 250 BEVs for the city government's vehicle fleet, thereby increasing the initial number of BEVs on the road[6]; and
5. *Hybrid policy:* Uses funds by providing 183 $10,000 incentives, installing 116 charging stations, and increasing the number of BEVs on the road at the start of the scenario by purchasing 83 for the government fleet.[7]

To assess their likely impacts, each scenario is simulated 250 times and their outcomes (i.e. the number of BEVs adopted) are

[2] In late 2014, the price of gasoline dropped dramatically, reaching a low of $2.208 per gallon in the United States in January 2015 (U.S. EIA, 2015) It has since partially rebounded and, as of October 2015, was $2.387. The $3.50-per-gallon price used in this simulation is closer to the five-year average price of gasoline in the United States.

[3] According to the 2005 census estimates, 12 U.S. cities have populations between 250,000 and 350,000. They received between $2.5 million (Plano, TX) and $20 million (St. Paul, MN) for energy and environment projects from ARRA (recovery.gov).

[4] Because the simulation is being done on a 100:1 scale, the number of subsidies actually programmed in the simulation is divided by 100, which was rounded up to 6.

[5] 240-volt Level 2 public chargers, which fully charge an EV in three to eight hours, cost an average of $9000 to install, accounting for permits (Yan, 2012). DC fast chargers can fully charge an EV in 30 min but cost about $55,000 to install. This scenario includes a combination of Level 2 and DC fast chargers at approximately a 1:6 ratio. Because the simulation occurs on a 100:1 scale, the number of chargers was divided by 100 and then rounded. Therefore, four chargers were included in the simulation.

[6] Assuming a $7,500 federal tax credit and a 20% bulk purchase discount, the cost of a BEV to the city was assumed to be $22,000. Because the simulation occurs on a 100:1 scale, the number of BEVs in the city fleet was divided by 100 and then rounded. A total of three BEVs were added as part of this policy scenario.

[7] The $5.5 million budget was divided evenly between incentives, chargers, and city fleet BEVs. Because the simulation occurs on a 100:1 scale, the number of incentives, chargers, and BEVs in the city fleet was divided by 100 and then rounded. A total of two incentives, one charger, and one BEV were added as part of this policy scenario.

Table 2.
A Description of the calculations and assumptions included in agents' simulated electric vehicle purchase-decision process.

A) Current vehicle age > assigned purchase age?
1. Every agent is assigned a vehicle with a randomly determined age. The age is based on a normal distribution with a mean of 60 months (five years) and a standard deviation of 20 months.
2. Every agent is assigned a vehicle purchase age. This is how old their car must be in order to purchase a new one. The purchase age is based on a normal distribution with a mean of 72 months (six years) and a standard deviation of 24 months.
3. With every round of simulation, the vehicles age increases by one month.
4. When a new vehicle is purchased, the vehicle age is reset to zero.

B) BEV car payment < 11% of monthly income?
1. BEV have a purchase price initially set at $35,000. This price is lowered in subsidy scenarios.
2. Home charging stations cost an additional $2000 to install.
3. Based on U. S. census 2009 estimates, each agent has an annual household income randomly assigned following a gamma distribution with a mean of $67,465 and a standard deviation of $66,700.
4. The monthly car payment was calculated using an interest rate of 4% on a 60-month loan.
5. The average American spends 11% of his or her gross monthly income on a car payment[a].

C) BEV range > 120% of average daily driving needs?
1. The average passenger vehicle travels approximately 29 miles a day and the average person travels 36 miles a day in a car[b]. We split the difference and randomly assign agents' daily travel distance along a normal distribution with an average of 32 miles.
2. Most commercially available BEVs have an advertised range of 100 miles. Because they often do not achieve this maximum and/or people may feel uncomfortable "running the battery dry," only agents whose average daily miles driven is less than 80 are able to be potential adopters.

D) Have alternative means to make longer necessary trips?
1. Separate from their average daily mileage, agents will occasionally need to make trips exceeding a BEV's 100-mile range. 10% of agents whose average daily mileage is within BEV range are modeled as needing to own a conventional vehicle to make less frequent longer trips. This parameter is randomly assigned.

E) Is the BEV cost effective?
The cost effectiveness of a BEV is determined by the following:
IF BEV price premium – [annual operating cost savings × years own BEV] < 0 THEN it is cost-effective to purchase a BEV where:
BEV price premium = (BEV purchase cost + charger cost – subsidy) – (cost of conventional vehicle)
Annual operating cost savings = [(gasoline price per gallon × annual miles traveled)/ vehicle mpg] – [cost to fully charge a BEV × annual miles traveled/ BEV range]
1. Using current electricity rates of $0.11 per kilowatt hour, it costs approximately $4 to fully charge a BEV (Krause et al., 2016). The assumed range of a BEV is 100 miles.
2. The price of gasoline is assumed to be $3.50 per gallon.
3. Based on results from the Indiana University Electric Vehicle Generation 1 survey[c], 42% of agents for which the BEV is cost effective will purchase a BEV. The other 58% of potential adopters may or may not purchase one, as a result of personal discount rates or other preferences. The latter group is funneled through the environmental and attitudinal questions to assess whether those characteristics enable remaining purchase barriers to be overcome.

F) Does agent have a strong environmental attitude?
Each agent is randomly assigned an "environmental" score based on a normal distribution. The 16% of agents with the highest scores are designated environmentalists and will adopt a BEV. This was selected as the environmentalist cut-off based on results from the Indiana University Electric Vehicle Generation 1[d] Survey (n = 2302) in which 16% of respondents "strongly agreed" with all of the following statements: "People need to change their lifestyles to protect the environment," "Climate change is a serious problem," and "Climate change is a result of human actions."

G) Is agent an innovator?
Each agent is randomly assigned an "innovation score" based on a normal distribution. Drawing from Rogers (2003), the approximately 2.5% of agents with the highest scores are designated innovators and are funneled toward adoption if they have seen any electric vehicle technology in their simulated environment.

H) Has the agent seen enough BEV technology to meet personal innovation comfort level?
Again drawing from Rogers (2003), the population is further divided up based on their innovation score and once agents have seen "enough" BEV technology to meet their comfort threshold, they are funneled toward adoption. Specifically, the following formula is used:
(BEVs seen + weights of charger awareness x chargers seen)/(all vehicles seen)

Table 2. (*continued*)

≥ …
… 2.5% for the ≈ 13.5% of the population who are early adopters
… 16% for the ≈ 34% of the population who are early majority
… 50% for the ≈ 34% of the population who are late majority
… 84% for the ≈ 16% of the population who are laggards
Sensitivity analysis is run where potential adopter agents that answered "yes" to questions F, G, or H (i.e. they are environmentalists, innovators, or have seen enough electric vehicle technology) are assumed to have a 90%, 75%, 50%, 25%, and 10% likelihood of adopting. The reported results assume a 10% adoption rate. This adoption rate was selected because it yields results that most closely approximate the market penetration rates predicted by NADA (2013) under status quo conditions and thus has external validity.

[c] U.S. Census, 2009
[a] Sahadi, 2003.
[b] U.S. DOT 2009.
[c] Carley, 2013.
[d] Graham et al., 2011

averaged across all runs. Each simulation spans a 35-year period, with every full rotation of agents representing one month. In sum, 75 distinct scenarios (5 policy scenarios × 15 sets of parameter specifications, including one set for the main model in the paper and 14 for the sensitivity analysis models) are each simulated 250 times.

3. Results and discussion

While the hypothetical investment of $5.5 million was the same for each of the simulated alternatives, the results suggest that the various policy interventions that local governments can pursue to promote the adoption of BEVs in their community are likely to have varying effects. The policies considered in this study yield notably different results in terms of the total number of BEVs present in a community at the end of the simulated timeframe. Although the point at which BEV usage reaches equilibrium appears relatively consistent across the scenarios, the results indicate that, holding public expenditures constant, the way communities choose to invest resources has a meaningful effect on the total number of electric vehicles adopted and in use at any given point in time. Fig. 3 shows the simulation results in terms of the estimated number of BEVs on the roadway in a community of 250,000 people over a 35-year period under each of the five policy scenarios. Under the baseline no-intervention scenario, the average number of BEVs on the road after equilibrium is reached, at close to the 10-year mark, was approximately 1890 (see Fig. 3) or 0.76%

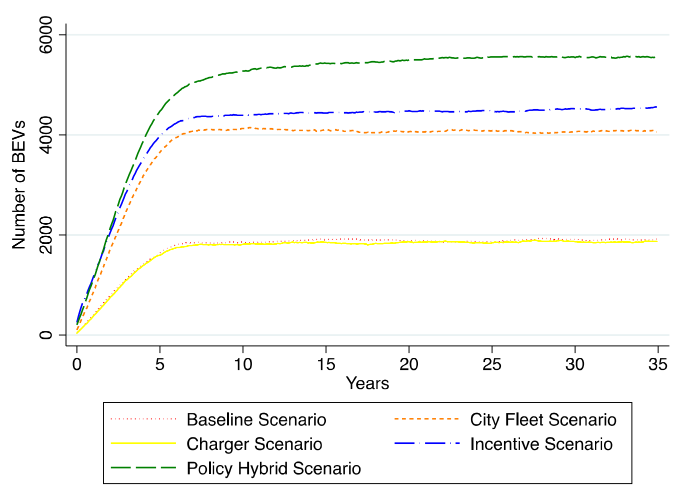


Fig. 3. Predicted growth in number of BEVs on roadway across five policy scenarios in a city with a population of 250,000.

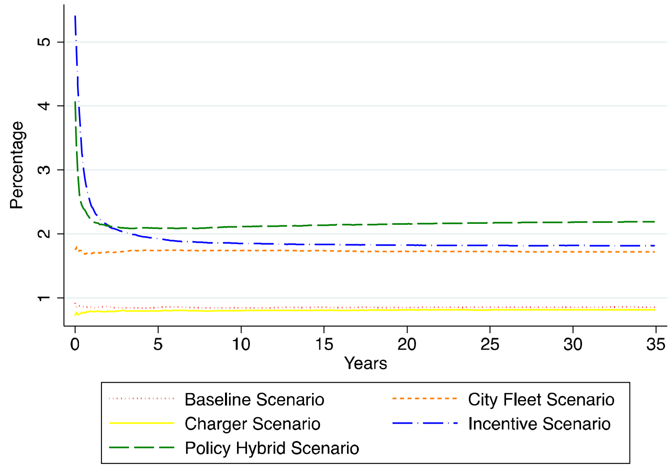


Fig. 4. BEV purchases as a percentage of total vehicle sales.

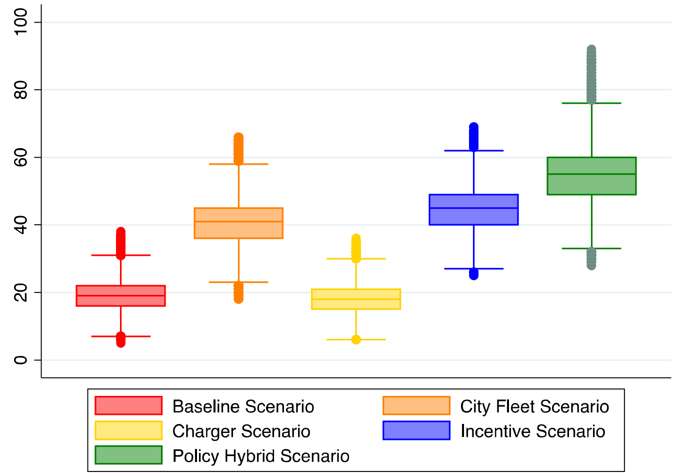


Fig. 5. Boxplot of the results of the 250 runs of each scenario.

of all vehicle sales (see Fig. 4). This is compared to 1850 (0.74%) in the charger scenario, 4075 (1.63%) in the city fleet scenario, 4470 (1.79%) in the incentive scenario, and 5490 (2.20%) in the hybrid scenario.

These results suggest three basic tiers of policy effectiveness, where increasing the charging network has virtually no impact, increasing vehicle visibility through the purchase of government fleets and providing incentives to reduce purchase price have similar moderate impacts, and the hybrid policy leading to the greatest number of BEVs on the roadways. The city fleet scenario increases the number of BEVs in the city at the start of the scenario, which increases the awareness of this technology among the drivers as they see these vehicles around the city. This increase in visibility preforms almost as well as the intervention that decreases vehicle cost and, so doing, increases the number of drivers who can afford a BEV. The incentive scenario, however, resulted in the fastest rate of BEV adoption, with the greatest numbers adopted during the first two years of the policy's implementation. Again, 550 credits each worth $10,000 were available under this scenario, and the rapid adoption occurred while they were available and slowed after they ran out. Although, compared to the city fleet intervention, the incentive intervention results in the adoption of 9% more BEVs over the course of the simulation's 35-year timeframe, a government's choice between these two options may ultimately best be based on the identity of the preferred direct beneficiary of government monies. Since the long-term social results from PEV adoption are relatively similar under both scenarios, a city government under financial strain or with an objective of increasing the energy efficiency of its own government operations might be wise to purchase vehicles for its own fleet rather than offer incentives to community members. However, the hybrid scenario, which combines these strategies, performs considerably better than either of the other policies do in isolation. It appears that these policy levers work synergistically to increase adoption through increased BEV familiarity.

As with any simulation, some variability in results is observed across the 250 runs of each scenario. The boxplot (see Fig. 5) shows that the interquartile range (IQR) and the 1.5IQR are symmetrical about the median for all scenarios. As expected, given the size of the dataset, each scenario has outliers. While there are outliers above and below the median, there are somewhat more outliers above then below the median for all scenarios. This observed variation may explain the unexpected result indicating that the charging station intervention actually reduced the number of BEV adoptions below the baseline, if only to a very small and statistically insignificant degree. As Fig. 5 shows, compared to the charger scenario, the results of the 250 simulated runs done for the baseline have a larger range and a greater number of outliers. This may have pulled its overall average up above the charger average, although not to enough to be outside the range of error.

Unlike Figs. 3 and 4 where the number of BEVs on the roadway reach an equilibrium as new ones replace old, Fig. 6 shows a count of the cumulative number of BEVs purchased over the 35-year simulation. It again shows that the supremacy of the hybrid scenario.

To illustrate the size of this effect, consider a city the size of Austin, Texas (population 885,400), where there are approximately 695,924 vehicles on the road. Table 3 compares the results across all policy scenarios, scaled up to the city of Austin. According to our simulation, the modest 0.87% difference between the baseline and city fleet scenarios in a city the size of Austin equates to approximately 6084 additional electric vehicles on the roadways at equilibrium. The largest difference, seen between the baseline scenario and the hybrid scenario is 10,018 BEVs, which is nearly a threefold increase.

The decision rules utilized in the model (see Fig. 2) describe four criteria that must be met for an agent to purchase a BEV. Agents that fail to meet any of these criteria are automatically modeled as purchasing a gasoline-powered vehicle. Agents that do meet all four of the criteria face several additional considerations that further influence their likelihood of purchasing a BEV, namely whether the BEV will be cost effective over the time that it is

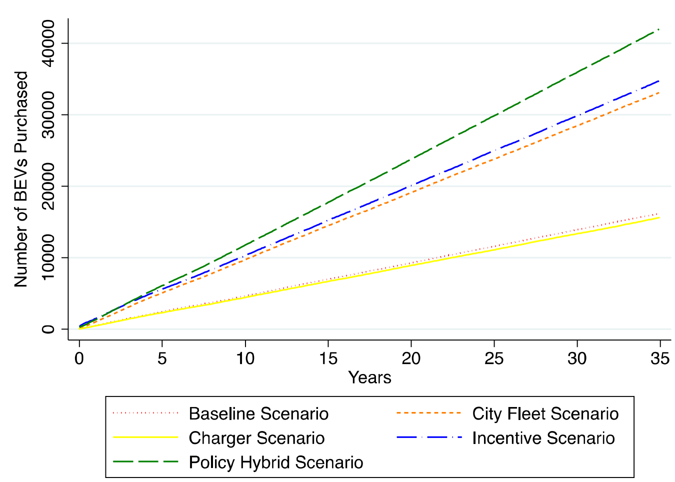


Fig. 6. Cumulative number of BEVs purchased in a city with a population of 250,000.

Table 3.
Simulation results in context of a city the size of Austin, Texas.

Scenario	Average number in simulation at equilibrium	Percentage of all vehicles	Number of vehicles in Austin, Texas
Baseline	18.9	0.76%	5262
Charger	18.5	0.74%	5152
City Fleet	40.8	1.63%	11,346
Incentive	44.7	1.79%	12,449
Hybrid	54.9	2.20%	15,280

owned by an agent, and the agent's individual environmental attitude and willingness to be a technology early adopter. These receive additional attention in the following description of results.

The first is cost effectiveness, which is a function of the BEV purchase price and operating cost relative to standard vehicles. Two of the simulated policy scenarios–incentive and hybrid–can influence BEV cost effectiveness. By offering subsidies that reduce the purchase price, a greater number of agents pass the threshold affordability criteria. Since the purchase price of a BEV is reduced (in this case by $10,000) the amount of money in operating costs that needs to be saved over its lifetime to recoup the price premium and make it cost effective is likewise reduced by that amount.

Fig. 7 looks directly at the role that cost effectiveness plays in BEV uptakes (see equation in Table 2). Of the 250,000 vehicles on the road, cost-effectiveness motivates the adoption of approximately 640 to 810, across all scenarios. Unsurprisingly, the incentive scenario yielded the largest increase in purchases based on cost-effectiveness considerations. All other scenarios, including the hybrid policy that also includes incentives, were found to be nearly identical.

Because BEVs are relatively expensive to purchase, their owners tend to be relatively wealthy. A rationale for incentive programs is to decrease their purchase price in order to encourage (somewhat) lower-income drivers to adopt BEVs. Fig. 8 shows the impact that the policy scenarios have on the average income of BEV drivers in the simulated community. At equilibrium, the average income of BEV drivers is approximately $131,000, with a between-scenario difference of approximately $2000. This suggests that the policy interventions, including those that offer subsidies, have little impact on encouraging individuals with lower incomes to adopt BEVs. Simply offering incentives that decrease the price of an initial number of BEVs did not encourage significant numbers of lower-income drivers to adopt BEVs. While incentives may initially increase the number of potential adopters, the results show that

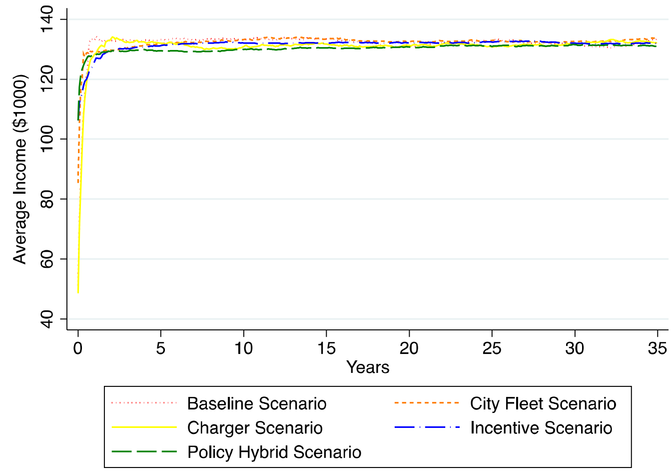


Fig. 8. Average income of BEV owners.

very few non-wealthy drivers used them. Further, none of the lower-income drivers that did use a rebate to buy a BEV could afford to replace it with another BEV because all rebates were used within the first six months of the simulation. Therefore, any income difference between the scenarios disappears by year five or six when the lower-income drivers replace their BEVs with gasoline-powered vehicles.

Different policy interventions may yield differential impacts across groups of agents as a result of their character traits. Strong environmental values may influence individuals to adopt an electric vehicle. However, reflecting the well-known attitude-behavior gap, environmental values alone are often insufficient to bring about pro-environmental behaviors. As such, environmental agents in our simulation must pass the identified threshold criteria. Based on the results of a survey administered to U.S. drivers by Carley et al. (2013) 16% of the population consider themselves “strong environmentalists.” In this study, it was assumed that strong environmentalists would purchase a PEV provided that they meet the cost and cost effectiveness thresholds. This subset of the simulated population is contained in Fig. 9. The hybrid policy scenario and provision of incentives increase the number of strong environmentalists that adopt BEVs and appear able to help bridge the attitude-behavior gap. The city fleet and charger policy interventions do not meaningfully change the purchasing decisions of strong environmentalist agents from what they are in the baseline scenario.

The five graphs in Fig. 10 group agents according to their

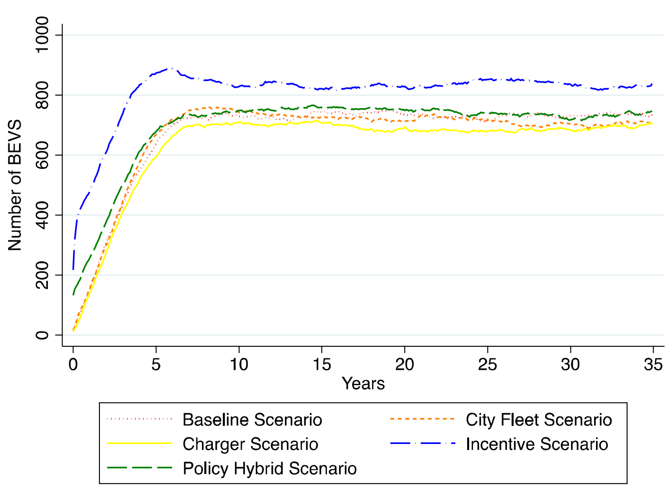


Fig. 7. The number of BEVs purchased due to vehicle cost-effectiveness in a city with a population of 250,000.

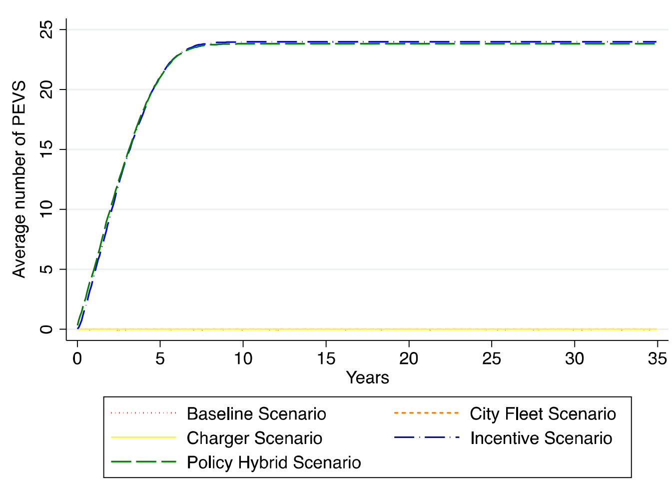


Fig. 9. Impact of policy interventions on purchasing decisions of strong environmentalists in a city with a population of 250,000.

Fig. 10. Average number of agents driving BEVs, by innovativeness classification in a city with a population of 250,000.[a] Since the number of agents in each innovation category is different, the comparison across innovation categories should be based upon adoption patterns and not on the numbers of those agents who adopt.

assigned propensity for innovation and show the impact generated by each policy intervention. Graphs 10A (innovators) and 10B (early adopters) contain agents that have above-average affinity for technology adoption. For agents in these two groups, there is little difference between any of the policy alternative scenarios and the baseline scenario. This indicates that, as expected, BEV adoptions among technophiles is driven more by awareness of BEV technology. Since the awareness thresholds for these two groups is so low, even the few BEVs included in the baseline scenario are enough for the technophiles to be aware of these vehicles.

A different adoption pattern appears among early majority adopters (Fig. 10(C)). While these drivers have a slightly higher-than-average affinity for technology, they wait until the technology becomes relatively mainstream before they buy. Once a sufficient number of more technology-loving motorists adopt BEVs, early majority drivers will begin to consider them as a viable option. Compared to the groups previously discussed, early majority drivers respond quite differently to the simulated policy interventions. Specifically, the city fleet scenario yields both the highest adoption rate and the greatest overall number of adoptions for this subset of the population. These results suggest that increasing the visibility of BEV technology by including them in government fleets is the best policy approach to increase their use among mainstream drivers. This conclusion is reinforced by the results of the scenario simulations for late majority drivers who are, to an even greater extent, only sensitive to seeing BEVs on the road (Fig. 10(D)). None of the other policy interventions have any impact on the purchasing behavior of members of this group. The final graph in Fig. 10 depicts adoption by laggards. No laggards adopted a BEV in any scenario.

The observed different responses that each of these groups of agents have to the simulated policy interventions has potentially important implications and suggest that policies be designed with their specific target populations in mind. "Innovators" and "early adopters" together comprise 16% of the total population (Rogers, 2003). By definition, these individuals will always be the first and the easiest group to persuade to adopt a new technology, but their absolute numbers are limited. Members of the early and late majority on the other hand together comprise 68% of the population. They tend not to adopt new technologies as quickly or fully, but their absolute numbers are greater and they are an important target population. Although somewhat different from the population as a whole, the results of the simulations suggest that the most effective way to encourage adoption by "mainstream" consumers is through frequent exposure to the technology, as is accomplished through the city fleet intervention.

4. Sensitivity analysis

ABM is based on input assumptions so running a sensitivity analysis of the simulation parameters is important to get a sense of the robustness of the results. While the parameters used in this study were derived from the literature, some degree of uncertainty remains. Therefore, this sensitivity analysis varies the following parameters: the percentage of those who determine that the BEV is cost effective and would consider purchasing one, the percentage of a driver's income that could be spent on a new vehicle, and the degree of economic segregation in each area of the city.

As described in Table 2, the initial simulation assumed that 42% of agents for which a PEV would be cost-effectives would purchase one. In the sensitivity analysis, this parameter was changed to 30%, 40%, 50%, 60%, and 70%. Although the overall number of BEV adoptions obviously changed across these scenarios, the overall pattern in the data and effect of the interventions did not differ substantively from the pattern using the 42%.

The simulations presented in this paper assume that drivers could only afford a BEV if the monthly payment was less than 11% of their monthly income. To test the impact of this assumption, this parameter was set to 5%, 10%, 15%, and 20% in the sensitivity analysis. Again, although the overall number of BEV adoptions obviously changed across these scenarios, the overall pattern in the data was generally the same as the pattern described in the result section of this paper. The hybrid scenario was the most effective at encouraging BEV adoption, followed by the incentive and city fleet scenarios and the charger scenario did not substantively differ from the baseline scenario. The one exception was where the threshold income percentage was set at 5%. In this circumstance, the incentive scenario was most effective and resulted in an average of 2% (or 28) more BEVs on the roadways as compared to the hybrid policy.

The economic integration/segregation scheme was also investigated in this sensitivity analysis. The scenarios investigated include complete economic segregation where all drivers lived in areas corresponding to their socioeconomic status as well as various degrees of integration. Specifically, integration models were run where 5%, 10%, 15%, and 20% of those in an income group were assigned to "live" in an area with a different socioeconomic level. This was also found to make no substantive difference on either the pattern of PEVs on the road or the pattern of the overall number of PEVs purchased.

5. Conclusions and policy implications

The objective of this study is to examine the relative impact that different policy interventions could have on the adoption of battery-powered electric vehicles (BEVs) in urban communities in the United States. Although replacing conventional gasoline vehicles with BEVs leads to public benefits including decreased urban air pollution and greenhouse gas emissions and increased energy security, it does not yield equivalent private benefits. As such, and as with all public goods, in the absence of supportive public policy, BEVs are likely to be adopted at rates below their social ideal (Weimer and Vining, 2011). In response, governments around the world are developing and implementing policies aimed at increasing consumer demand (Lane et al., 2013; Sierzchula, 2014). We identify a set of general public policies and assess rates of BEV adoption under simulated scenarios where they are implemented and compare their outcomes to a no-policy baseline. All of the policy scenarios are based on an expenditure of $5.5 million and include using that money to purchase BEVs for their city fleet, offer incentives to lower BEV purchase price, install public charging stations, or pursue a hybrid approach by using the funds to provide a mix of fleet vehicles, incentives, and chargers. The results show that the most effective policy options was the hybrid policy scenarios. Approximately three times as many drivers adopted BEVs when this policy was in place than under the baseline scenario. This policy increases the visibility and familiarity of BEV technology in the community by increasing the number of BEVs on the street via the city fleet and by lowering the cost of ownership via financial incentives. This policy alternative may help normalize BEVs as a driving option and counter the idea that they are not a viable alternative to gasoline-powered vehicles.

Although they increase BEV adoption over the baseline condition, the city fleet and incentive and scenarios remain somewhat less successful than the hybrid policy alternative. While the city fleet scenario had the largest effect on the actions of mainstream consumers, i.e. those who fall in the early and late majority innovation categories, it is not as effective for the population as a whole as those that offer some purchase incentives. The rationale for offering incentives is to lower the overall cost of the BEV, thereby increasing cost effectiveness and the overall number of potential purchasers. However, the fact that any potential BEV purchaser can use the incentives, not just those with financial need, means that incentives do not appreciably increase the number of actual adopters. Indeed, wealthy agents, able to buy the vehicles at their full sticker price, may utilize the majority of the incentives. Moreover, the less wealthy agents that purchased a BEV with the assistance of an incentive would not able to replace it with another after the incentives ran out.

Rogers (2003) suggests that persons will only adopt new technology based on the interplay between their own internal feelings toward the new technology and their awareness of the product itself. Since governments cannot directly influence citizen innovativeness, the only lever that they can utilize to attract new purchasers in this regard is to increase awareness. In this model, awareness is increased as individuals see BEVs on the road and, to a lesser extent, see public charging stations. Awareness of the technology gained through other means such as private-sector marketing, public service announcements, and news stories are not included in this simulation. Further exploration of marketing as a means to encourage BEV adoption should be considered in future work.

Agent-based models all face significant verification and validation challenges. Due to a lack of historical data on BEV adoption, we are unable to validate every aspect of the model. However, the parameters we used to quantify the influences on BEV purchases are grounded in empirical data and resulted in a reasonable simulation output. Although not ideal, this limited approach toward model validation has been used in previous ABM studies on electric vehicles (Sweda and Klabjan, 2011) and may continue to be relied on until more BEV sales data is obtained.

With further development, the findings presented here can have an important impact on policy makers as they attempt to encourage BEV adoption. While we readily acknowledge that simulations do not predict the adoption of BEVs in a real city, the assumptions made in this model are reasonable, and as such, provide a solid exploration of the four policy alternatives analyzed. Since governments cannot readily experiment with such alternatives within their jurisdictions without incurring significant costs, simulations provide a theoretical understanding of the complex dynamics underlying the decision to purchase a BEV and the government's policy alternatives that could help encourage that choice.

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