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A generalized dynamic discrete choice model for green vehicle adoption

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ABSTRACT

Much is happening in the automotive industry and new models are in the market or are expected to be available soon. At the same time, environmental awareness, new regulations for increased fuel efficiency, and the need to diminish greenhouse gas emissions make small vehicles and alternative fuel vehicles more competitive. As a consequence, vehicle characteristics and consumer decisions will change rapidly in the short and medium run. Accounting for the dynamic of the problem is important to correctly forecast green vehicle acceptance and to evaluate eco-friendly policies. This paper proposes a generalized dynamic discrete choice approach that models purchase behavior and forecasts future preferences in a finite time horizon setting. The framework allows one-time purchases, repeated purchases, univariate and multivariate diffusion processes that capture the evolution of vehicle characteristics and dynamics in the market conditions. The models proposed are estimated using stated preference data collected in Maryland. Results show that the formulation with repeated purchases successfully captures changes in the market shares, and that the multivariate diffusion process adopted to model the evolution of fuel prices further improves both model fit and the ability to recover peaks in demand. The estimated coefficients have been applied to test different policy scenarios, including changes in fuel prices, vehicle purchase prices, and improvements of car characteristics. These policies have a high impact on the adoption of electric cars and on their diffusion in the marketplace.

1. Introduction

The choice of a specific durable good is not only influenced by the characteristics of the good itself, but also by industry evolution, development of new technology, government regulation, an individual's social network, change in personal attitude, etc. (Lorincz, 2005). In the context of vehicle purchasing, consumer behavior highly depends on fuel price and its volatility (Goodwin et al., 2004), innovations in the vehicle market (Schiraldi, 2011; Cirillo et al., 2015), increasing awareness about environmental issues (Flamm, 2009; Flamm and Agrawal, 2012), friends' and families' travel behavior (Farber and Páez, 2009), and policies and taxes introduced by local and national authorities (Hayashi et al., 2001; Feng et al., 2005). In recent years, more fuel-efficient vehicles or alternative energy sources are available in the market and their characteristics are expected to change over time as technology develops. Considering that vehicle characteristics evolve rapidly with time, consumers choose to buy a vehicle or not in order to maximize the expected utility over the current and future periods (Cirillo and Xu, 2011). However, in transportation planning, static models are usually used to estimate vehicle ownership and type, ignoring the dynamics in vehicle attributes and the evolution of taste and preferences. Therefore, a dynamic framework is necessary to model vehicle purchase behavior, especially adoption of more efficient

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vehicle or vehicle running on alternative fuels.

Dynamic discrete choice models (DDCMs) of demand for durable goods were started by researchers in economics and social science. Rust (1987) was the first to formulate a dynamic logit model by proposing a method based on dynamic programming. His model was applied to estimate the optimal stopping time to replace a used bus engine. Melnikov (2013) expanded the engine replacement model to capture the purchasing behavior of printer machines. He applied the optimal stopping problem to model the decision of whether to buy a printer machine or to postpone the purchase based on the expected evolution of the product quality and price, incorporating consumer heterogeneity and considering inter-temporal incentives of market participants. Recently, Cirillo et al. (2015) introduced a dynamic discrete choice formulation for vehicle ownership analysis. Specifically, the proposed structure intends to capture not only the optimal purchase time but also consumer's choices on vehicle types in a dynamically changing vehicle market. They formulated the timing of consumer's purchase decision as a regenerative optimal stopping problem. The model explicitly accounts for consumer's forward-looking behavior and market evolution such as the changes in gasoline price or electric vehicle price. However, their model is limited to repeated purchases, and is only capable of incorporating one evolving dynamic attribute at a time.

The work proposed in this paper generalizes the DDCM of Cirillo et al. (2015) and presents three major innovations. First, the proposed model is able to capture the purchase pattern of different durable goods in the market, allowing for both one-time purchase (agents are out-of-market once a purchase is made) and repeated purchases (agents are always in the market). Second, it relaxes the assumptions on the number of forward-looking time periods. Last, to model the industry evolution the proposed model incorporates a stochastic diffusion process that accounts for multiple interdependent attributes changing over time. The approach contributes to the state of the art by modeling jointly vehicle purchase time and vehicle type choice in a finite time horizon. The proposed DDCM is estimated on the data from a web-based stated preference survey which was designed to analyze households' future vehicle preference in the Maryland area.

The remainder of this paper is organized as follows. Section 2 reviews the previous literature on DDCMs with applications in economics and transportation. Section 3 presents the methodology and formulates the dynamic structures for different scenarios: one-time purchase, repeated purchases, one evolving attribute, and multiple interdependent evolving attributes. Section 4 introduces the stated preference panel data for model estimation, while Section 5 presents model estimation results. Model validation and sensitivity analysis are given in Section 6. The final Section offers concluding remarks and avenues for future research.

2. Literature review

2.1. DDCMs in economics

DDCMs are widely used in economics and related fields. They are useful tools for the evaluation of price elasticity, intertemporal substitution, and new policies in durable goods markets. In the structure of DDCMs, agents are forward-looking and maximize expected intertemporal payoffs, with the knowledge of the evolving nature of product attributes such as price and technology. The earliest generation of research on DDCMs includes Wolpin (1984) on fertility and child mortality, Miller (1984) on job matching and occupational choice, Pakes (1984) on patent renewal, and Rust (1987) on machine replacement. Although the computational complexity of model estimation represents a clear impediment to the development of these dynamic structures, a significant number of interesting applications aiming at solving the empirical issues have appeared in different areas of economics, e.g., permanent unobserved heterogeneity, initial conditions, censored outcomes and sample selection, measurement error, endogeneity, identification, etc. (Aguirregabiria and Mira, 2010).

With his pioneering work in dynamic modeling, Rust (1987) was the first to formulate the optimal stopping problem and to estimate the optimal time to replace a bus engine. The model was conceived for a single agent, a homogeneous product, and infinite time horizon; random components were assumed to be additively separable, conditionally independent and extreme value distributed. Melnikov (2013) expanded Rust's model to consider a binary decision, whether to buy or to postpone the purchase, based on the expected evolution of printer's quality and price. In his dynamic structure, Melnikov considered heterogeneous products and homogeneous consumers. He assumed that consumers will be out-of-market once they make a purchase, and random components are independently distributed over consumers, products, and time periods. Lorincz (2005) extended the Rust model by proposing the so-called persistent effect, which allows consumers who already had a product to upgrade it instead of replacing it.

Knowing the importance of incorporating consumer heterogeneity, the dynamic structure was further improved in a series of later papers (Berry et al., 1995; Shcherbakov, 2016; Carranza, 2010; Gowrisankaran and Rysman, 2012; Dubé et al., 2012). Berry et al. (1995) showed that it is necessary to consider consumer heterogeneity to obtain realistic predictions of elasticity and welfare. Their model includes random coefficients, accounts for market-level demand shocks, and endogenous prices, but is static in nature. Dubé et al. (2012) recast Berry's estimation as a mathematical program with equilibrium constraints to avoid numerical issues associated with the standard nested fixed point (NFP) algorithm and to make the estimation process more efficient. Gowrisankaran and Rysman (2012) analyzed consumer's preferences over digital camcorder products by combining Berry's modeling techniques of consumer heterogeneity and Rust's optimal stopping technique. Their model explicitly accounted for dynamics in consumer behavior and allowed for unobserved product characteristics, repeated purchases, endogenous prices, and multiple differentiated products. Another interesting extension of Rust's bus engine replacement model was the integration of an auto-regressive process of order n (AR(n)) type serial correlation of error components into the dynamic structure (Reich, 2013). To make the estimation process more efficient, Reich (2013) decomposed the integral over the unobserved state variables in the likelihood function into a series of lower dimensional integrals, and successively approximated them using Gaussian quadrature rules. More recently, DDCMs have been developed and applied to many other areas such as demand for housing (Bayer et al., 2016), emergency evacuation (Serulle, 2015), and car ownership and purchase decision (Schiraldi, 2011; Cirillo et al., 2015).

2.2. Dynamic applications of car ownership

Dynamic structures for car ownership include: dynamic transaction and duration models (Gilbert, 1992; De Jong, 1996; Bhat and Pulugurta, 1998; Mohammadian and Miller, 2003; Rashidi et al., 2011), models based on stated preference (SP) data (Brownstone et al., 2000; Hensher and Greene, 2001; Abbe et al., 2007), models that account for past behavior and that use lagged variables (Ben-Akiva et al., 2007; Nolan, 2010), and approaches based on dynamic programming with forward-looking agents (Schiraldi, 2011; Cirillo et al., 2015; Glerum et al., 2013; Gillingham et al., 2015).

Duration models mainly aim to capture dynamics in car ownership, and are used especially to forecast households' vehicle transaction behavior. Gilbert (1992) proposed a hazard model to estimate the distribution of automobile ownership length, and the effects of car characteristics, socioeconomics and market attributes on vehicle holding. De Jong (1996) calibrated a car ownership model system to estimate household's vehicle holding, choice of vehicle type, annual vehicle miles traveled, and fuel efficiency. He adopted a stochastic duration model based on a hazard function to predict the length of vehicle holding. This model was later combined with the Dutch Dynamic Vehicle Transaction Model (DVTM) to account for car disposal without replacement. Duration models for the time between vehicle transactions have also been used to explain the total number of cars in a household (Bhat and Pulugurta, 1998). Mohammadian and Miller (2003) proposed a market-based transaction approach to solve inconsistency in observed choices. They employed a mixed logit model to investigate the effects of heterogeneity in the dynamic transaction model and to distinguish between heterogeneity-based and state-dependence-based effects for the observed persistence in choice behavior. Rashidi et al. (2011) estimated a system of hazard-based equations in which timing of residential relocation, job relocation and vehicle transaction were selected as endogenous variables.

The availability of high-quality panel data is always a challenging issue for the calibration and validation of dynamic models. Revealed preference (RP) panel and pseudo-panel data have been widely used in dynamic models for car ownership. However, both of them have limitations. For panel data, the size and representativeness of the samples decline over time due to attrition, so the data sets are often small (Hanly and Dargay, 2000). An important disadvantage of pseudo-panel data is that averaging over cohorts transforms discrete values of variables into cohort means, therefore individuals' information is lost (Dargay and Vythoulkas, 1999). Due to these limitations, many researchers started to use SP panel data and the combination of SP and RP data for dynamic model estimation. Brownstone et al. (2000) used RP and two waves of SP data to estimate demand for vehicles with alternative fuels. The joint model estimated on both RP and SP data was found to be superior to other specifications. The SP part provides essential information about attributes not available in the marketplace, while the RP part guarantees a plausible model for forecasting. Considering new car types or technologies not commonly used in the marketplace, Hensher and Greene (2001) modeled transactions with new vehicle types which required the collection of SP data. Abbe et al. (2007) studied household vehicle usage, including the potential gains from alternative fuel vehicles, to forecast vehicle emissions using a SP survey on electric vehicle usage. All existing studies based on SP data aim at forecasting market shares for new car types and individual preferences, but are incapable to predict when choices will be made over time (Cirillo et al., 2015).

In transportation, the majority of DDCMs account for consumer's previous actions such as inertia effect. Future plans and random changes in the market conditions are usually not accounted for. Ben-Akiva et al. (2007) proposed a DDCM with the integration of Hidden Markov Chain to model sequence of choice decisions and the evolution of latent variables. The model, applied to driving behavior analysis, models behavioral dynamics such as individuals' plans, well-being states, and previous actions. Nolan (2010) estimated a dynamic random effects probit model on a micro-level longitudinal data to analyze the determinants of household car ownership in Ireland. This model considers impact from correlated effects, state dependence, unobserved heterogeneity, and initial conditions.

Consumers' expectation and market evolution over time are essential to model purchase decisions in current and future vehicle markets. Although sometimes the future effects are not fully known, or depend on factors that have not yet transpired, it can be assumed that individuals will maximize utility among the available alternatives at that time (Cirillo and Xu, 2011). This knowledge enables consumers to choose the alternative in the current period that maximizes his expected utility over the current and future periods (Train, 2003). Schiraldi (2011) was the first to introduce a dynamic structural approach with optimal stopping problem to study car replacement decisions in a second-hand vehicle market in Italy. His model accounts for consumer's heterogeneity, future expectation, price endogeneity, and infinite time horizon. However, the model is based on aggregate historical data not allowing attributes to change dynamically over time. To overcome this limitation, Cirillo et al. (2015) proposed a DDCM with regenerative optimal stopping formulation in order to capture not only the optimal car purchase time but also consumer's choices on vehicle types in a dynamically changing vehicle market. Glerum et al. (2013) extended Cirillo's discrete choice model to a dynamic discrete-continuous car ownership model to jointly estimate vehicle transaction type, annual distance driven, and fuel type of each household car. The choice of annual driving distances (considered as myopic), depending on the number and type of household cars (consider forward-looking behavior), was modeled with a constant elasticity of substitution (CES) utility. Gillingham et al. (2015) developed a dynamic structural micro-econometric model to estimate household vehicle ownership, type choice, and usage in Denmark. They explicitly modeled the choice between scrapping the car or selling it on the used-car market, with the consideration of endogenous equilibrium prices and forward-looking behavior in a finite time horizon. Fosgerau et al. (2013) developed the recursive logit model and was the first to apply it to optimal route choice problem by formulating each path as a sequence of link choices. At each node a decision maker chooses the utility-maximizing outgoing link with link utilities given by the instantaneous cost, the expected downstream utility identified by Bellman equations. The recursive logit model corresponds to a DDCM (Rust, 1987) and can be applied to dynamic car ownership analysis.

3. Methodology: dynamic model formulation

In this Section, we present the formulation of the dynamic framework, the specification of the dynamic attributes, and the estimation strategies for solving the underlying Maximum Likelihood problem.

Consumers are indexed by $i = 1,2,...,M$. Time is assumed to be discrete and indexed by $t = 0,1,...,T$. In each time period t, consumer i faces two options if he or she is in the market: (a) to buy one of the products $j \in \mathscr{I}_t = \{1,2,...,J_t\}$ available in the market at time t and obtain a terminal payoff u_{ijt}; or (b) to postpone the purchase and obtain a one-period utility payoff $c_{it}(x_{it},q_{it};\theta_i,\alpha_i)$, where x_{it} is a vector of social demographic attributes for consumer i at time t, q_{it} is a vector of characteristics of consumer's owned products, θ_i and α_i are vectors of parameters corresponding to x_{it} and q_{it}.

If consumer i buys product $j \in \mathscr{I}_t$, he or she obtains a terminal payoff formulated as follows:

$$u_{ijt} = f(x_{it},z_{jt},y_{jt};\theta_i,\gamma_i,\beta_i) + \varepsilon_{ijt}, \tag{1}$$

where x_{it}, θ_i are $(1 \times Q)$ vectors defined as above.

z_{jt} is a $(1 \times K)$ vector of static or time-dependent characteristics for product j in the market in time period t, and γ_i represents a vector of corresponding parameters.

y_{jt} is a $(1 \times H)$ random vector of dynamic attributes for product j in the market in time period t, such as energy price, vehicle price, and environmental incentives which describe industry/market evolution. β_i represents a vector of parameters related to y_{jt}.

ε_{ijt} is an individual-specific random utility component, which follows generalized extreme value (GEV) distribution. We assume these random utility components are independently and identically distributed (i.i.d.) over consumers, products, and time periods.

We assume consumer preferences on characteristics of products are homogenous, then parameters $\theta_i,\gamma_i,\beta_i$ reduce to θ,γ,β respectively. Specifically, if consumer i decides to buy a vehicle at time t instead of postponing, vehicle type choice is estimated by a multinomial logit (MNL) model with an error component following type 1 extreme value (EV1) distribution. Correspondingly, for each consumer i, $v_{it} = max_{j\in\mathscr{I}_t} u_{ijt}$ follows EV1 distribution with cumulative distribution (F_v) and probability density functions (f_v) as follows:

$$F_v(u;r_{it}) = \exp(-e^{-(u-r_{it})}), \tag{2}$$

$$f_v(u;r_{it}) = e^{r_{it}}\exp(-e^{-(u-r_{it})}-u), \tag{3}$$

where r_{it} is the mode of this distribution, formulated as:

$$r_{it} = \ln G(\exp(f(x_{it},z_{jt},y_{jt};\theta,\gamma,\beta))), \tag{4}$$

where $G(f(x_{it},z_{jt},y_{jt};\theta,\gamma,\beta)) = \sum_{j\in\mathscr{I}_t} f(x_{it},z_{jt},y_{jt};\theta,\gamma,\beta)$ for MNL model with a Gumbel-distributed error component. Alternatively, r_j can be represented as follows:

$$r_{it} = ln\sum_{j\in\mathscr{I}_t} exp(f(x_{it},z_{jt},y_{jt};\theta,\gamma,\beta)) = E_t[\max_{j\in\mathscr{I}_t}(u_{ijt})] = E_t[v_{it}], \tag{5}$$

where $E_t(*)$ is the expectation given vehicle set $\mathscr{I}_t$ in the market. We consider r_{it} because it is a scalar-valued sufficient statistic for the distribution of future payoffs (Melnikov, 2013), and it contains the information available to the consumer i at time t.

In each time period, and based on the available information, the consumer is called to decide when to buy a vehicle and which type of vehicle to buy. The frameworks models jointly the decisions of whether to postpone the purchase until the next period or to buy a new vehicle; in the latter case the consumers also chooses product j_t^* from $\mathscr{I}_t$ that maximizes his or her utility of purchase (u_{jt}). We assume consumers are able to look forward and maximize their expected inter-temporal payoffs. Denoting the time period the consumer decides to buy a product by τ, the consumer's optimization problem can be formulated as:

$$D_{it}(v_{it},r_{it},c_{it}) = max_{\tau\geqslant t}\{\sum_{k=t}^{\tau-1}\beta^{k-t}c_{ik} + \beta^{\tau-t}E_\tau[v_{i\tau}|r_{it}]\}, \tag{6}$$

where D_{it} represents the decision process of consumer i at time t; $\beta \in [0,1]$ is a common discount factor; and $E_\tau[*|r_{it}]$ denotes a conditional expectation given the information set available for consumer i at time t.

Given the definition of v_{it},r_{it},c_{it}, an alternative way to formulate the consumer's decision process recursively is as follows:

$$D_{it}(v_{it},r_{it},c_{it}) = \max\{v_{it},c_{it} + \beta E_{t+1}[D_{it+1}(v_{it+1},r_{it+1},c_{it+1})|r_{it}]\}, \tag{7}$$

If consumer i postpones his or her purchase at time t, the reservation utility can be written as:

$$W_{it}(r_{it}) = c_{it} + \beta E_{t+1}[D_{it+1}(v_{it+1},r_{it+1},c_{it+1})|r_{it}], \tag{8}$$

Therefore, the recursive formulation of the consumer decision process can be simplified as:

$$D_{it}(v_{it},r_{it},c_{it}) = \max\{v_{it},W_{it}(r_{it})\}, \tag{9}$$

The consumer's decision D_{it} remains random because the random component ε_{ijt} exists in the utility function. We assume ε_{ijt}

randomly take a specific realization for each consumer i, which indicates ε_{ijt} is simply the unobserved part of the utility function and is independent of dynamic attributes. Based on utility maximization, consumer i will make a purchase at time t when $v_{it} > W_{it}(r_{it})$. Otherwise, he or she will postpone the purchase until the next period. For a randomly choosing consumer i, the probability of postponing the purchase at time t can be written as:

$$\pi_{i0t}(r_{it}) = P(v_{it} \leqslant W_{it}(r_{it})) = F_v(W_{it}(r_{it});r_{it}) = \exp(-e^{-(W_{it}(r_{it})-r_{it})}), \tag{10}$$

Consequently, the probability that consumer i buys a product at time t is $h_{it}(r_{it}) = 1-\pi_{i0t}(r_{it})$. And the probability of the consumer purchasing j at time t is the product of $h_{it}(r_{it})$ and the conditional probability of choosing $j \in \mathscr{I}_t$ given consumer i makes a purchase.

$$\begin{aligned}\pi_{ijt}(r_{it}) &= P([v_{it} > W_{it}(r_{it})] \cap^{[} v_{it} = u_{ijt}]),(11)\\ &= P(v_{it} > W_{it}(r_{it}))\cdot P(v_{it} = u_{ijt} \geqslant u_{ikt}\ ,\forall\ k \in \mathscr{I}_t\ and\ k \neq j)\\ &= h_{it}(r_{it})\cdot P(u_{ijt} \geqslant u_{ikt}\ ,\forall\ k \in \mathscr{I}_t\ and\ k \neq j)\\ &= h_{it}(r_{it})\cdot p_{ijt}\end{aligned} \tag{11}$$

where p_{ijt} represents the conditional probability of buying product j given that consumer i makes a purchase at time t. Obviously, if the consumer makes a purchase, $\sum_{j\in\mathscr{I}_t} p_{ijt} = 1$; otherwise, $\sum_{j\in\mathscr{I}_t} p_{ijt} = 0$.

It should be noted that the calculation of the expected utility in the future is based on a finite horizon scenario tree. At each time period, we assume a respondent can anticipate the possible alternative characteristics over a limited number of future time periods. For example, if three future time periods are considered, the respondent is assumed to have no knowledge of the 4th time period starting from time 0, and the expected utility from the 4th time period is assumed to be zero. For more details, we refer to Cirillo et al. (2015).

In the following sub-Sections the general framework described above will be generalized in order to relax some of the assumptions and to accommodate different behavioral processes. In particular, we formulate model for one-time purchases and repeated purchases and industry evolution based on one dynamic attribute and multiple correlated dynamic attributes.

3.1. Scenario 1: One-time purchase

In this case, we assume that consumers can only make one purchase in the considered time horizon and will leave the market immediately after their first purchase. We will use the probability transition matrix of vehicle ownership as an example to describe this scenario in detail. Denoting vehicle ownership status of consumer i at time t by $S_{it} \in \{0,1,2,3,4\}$, where $S_{it} = 0$ if the consumer does not purchase any vehicle, $S_{it} = 1$ if buys a gasoline vehicle, $S_{it} = 2$ if buys a hybrid vehicle, $S_{it} = 3$ if buys an electric vehicle, and $S_{it} = 4$ if the consumer is out-of-market. The transition of consumer states is governed by a Markov probability matrix H_1: $\{0,1,2,3,4\} \to \{0,1,2,3,4\}$ specified as:

$$H_1(r_{it}) = \begin{bmatrix} \pi_{i0t}(r_{it}) & \pi_{i1t}(r_{it}) & \pi_{i2t}(r_{it}) & \pi_{i3t}(r_{it}) & 0\\ 0 & 0 & 0 & 0 & 1\\ 0 & 0 & 0 & 0 & 1\\ 0 & 070 & 0 & 1 & \\ 0 & 0 & 0 & 0 & \end{bmatrix}, \tag{12}$$

If the consumer does not purchase any vehicle, $S_{it} = 0$, he or she has a probability of $\pi_{i1t}(r_{it})$, $\pi_{i2t}(r_{it})$, or $\pi_{i3t}(r_{it})$ to purchase a gasoline, hybrid, or electric vehicle, and a probability of $\pi_{i0t}(r_{it})$ to postpone the purchase to the next time period. If the consumer makes a purchase, $S_{it} = 1,2,\ or\ 3$, he or she will be out-of-market where $S_{it} = 4$. Intuitively, state 4 is an absorbing state, which indicates that once the consumer is out-of-market, he or she will never return.

3.2. Scenario 2: Repeated purchases

Notice that the model in scenario 1 can be extended to incorporate repeated purchases, that is, the consumer will stay in market or return to market after buying a product. More specifically, repeated purchases can be modeled by solving a regenerative optimal stopping problem. When the consumer reaches a terminal state, the decision process is restarted and attributes describing characteristics of the consumer's owned product are reinitialized. Note that "regenerative" takes its statistical meaning (Ross, 1997), so it is sufficient to discuss the sequence of choices from one regeneration time to the next. Taking vehicle ownership problem as an example, if consumer i always stays in market, the transition of consumer states can be represented by a Markov probability matrix H_2: $\{0,1,2,3\} \to \{0,1,2,3\}$:

$$H_2(r_{it}) = \begin{bmatrix} \pi_{i0t}(r_{it}) & \pi_{i1t}(r_{it}) & \pi_{i2t}(r_{it}) & \pi_{i3t}(r_{it})\\ q_{10} & (1-q_{10})p_{i1t} & (1-q_{10})p_{i2t} & (1-q_{10})p_{i3t}\\ q_{20} & (1-q_{20})p_{i1t} & (1-q_{20})p_{i2t} & (1-q_{20})p_{i3t}\\ q_{30} & (1-q_{30})p_{i1t} & (1-q_{30})p_{i2t} & (1-q_{30})p_{i3t} \end{bmatrix}, \tag{13}$$

where q_{j0} represents the transition probability from state j to state 0. In this case, whether a consumer makes a purchase or not, he or she will have a chance to buy or postpone to buy. In the diverse market of durable products, a consumer usually does not consider repurchase immediately after owning a new product. Therefore, in a more comprehensive framework, when a consumer buys a product, he or she will be out-of-market for a certain time period and then return to market.

3.3. Scenario 3: A single dynamic attribute involving in industry evolution

As defined in Section 3, y_{jt} represents the evolution of product j's characteristics in the market or environmental incentives offered by producers or policy makers. Given the dimensionality of the product characteristic space and the diversity of products in a typical market, it is computationally infeasible to generate y_{jt} directly (Melnikov, 2013). Therefore, we assume that a reduced set of state variables can adequately describe the state of the market at time t. In this case, we model a single dynamic attribute by a diffusion process which is commonly used in stochastic growth models.

$$y_{j,t+1} = \mu(y_{jt}) + \sigma(y_{jt})\upsilon_{j,t+1}, \tag{14}$$

where $\upsilon_{j,t+1}$ are i.i.d. and follow standard normal distributions; $\mu(y_{jt})$ and $\sigma(y_{jt})$ are continuous and almost everywhere differentiable; $0 < \sigma(y_{jt}) < \infty$; $\mu(y_{jt}) > y_{jt}$; and $\lim_{n\to\infty}\beta^n\mu^n(y) < \infty$ where $0 \leqslant \beta < 1, \mu^0(y) = \mu(y), \mu^n(y) = \mu(\mu^{n-1}(y))$.

Notice that the above formulation is quite flexible and encompasses many specifications used to model economic growth and technological change. Considering the dynamic pattern in vehicle ownership problem, we use a stable auto-regressive process of order one (AR(1)), a specific type of diffusion process, to generate state variables such as energy price and vehicle price. The AR(1) specifies that the dynamic variable depends linearly on its own previous values and a stochastic term. The formulation can be expressed as follows:

$$y_{j,t+1} = \delta_j + \eta_j y_{jt} + \sigma\upsilon_{j,t+1}, |\eta_j| < 1, \tag{15}$$

where δ_j and η_j are parameters to be estimated, σ is the standard deviation of the stochastic term.

3.4. Scenario 4: Multiple correlated dynamic attributes involving in industry evolution

The AR(1) process in Scenario 3 can be extended to a vector auto-regressive process of order one (VAR(1)) to incorporate multiple correlated dynamic variables in market evolution. The VAR(1) is a generalized form of AR(1). It captures the linear interdependencies among multiple time series variables by building the evolution of one variable on its own lags and the lags of the other variables. In the case of two correlated dynamic variables, the process can be specified as follows:

$$y_{1,t+1} = \delta_1 + \eta_{11}y_{1,t} + \eta_{12}y_{2,t} + \sigma_1\upsilon_{1,t+1}, \tag{16}$$

$$y_{2,t+1} = \delta_2 + \eta_{21}y_{1,t} + \eta_{22}y_{2,t} + \sigma_2\upsilon_{2,t+1}, \tag{17}$$

where $\delta_1, \delta_2, \eta_{11}, \eta_{12}, \eta_{21}, \eta_{22}$ are parameters to be estimated; σ_1 and σ_2 are the standard deviations of the stochastic parts. Alternatively, the process can be written in a matrix form:

$$y_{t+1} = B + Ay_t + \epsilon_{t+1}, \tag{18}$$

where $B = \begin{bmatrix}\delta_1\\ \delta_2\end{bmatrix}$ and $A = \begin{bmatrix}\eta_{11} & \eta_{12}\\ \eta_{21} & \eta_{22}\end{bmatrix}$ are parameters to be estimated; ϵ_{t+1} is the stochastic term which follows multivariate normal distribution with mean $\begin{bmatrix}0\\ 0\end{bmatrix}$ and variance $\begin{bmatrix}\sigma_1^2 & \sigma_1\sigma_2\\ \sigma_1\sigma_2 & \sigma_2^2\end{bmatrix}$.

We present four scenarios of model structures to identify different purchase behaviors and markets. The combinations of these scenarios can also be used to model more complex market situation. This DDCM is estimated by a maximum likelihood technique. The estimated parameters of $\theta,\alpha,\gamma,\beta$ are obtained by maximizing the likelihood of purchase decisions over all the consumers and time periods.

4. Data description

The data used for the empirical analysis was collected from a self-interview, web-based stated preference survey, which was designed to analyze households' future preferences on new vehicle adoption in a dynamic market (Cirillo et al., 2017). The stated choice experiment places respondents in a hypothetical nine-year future time period from 2014 to 2022. Each year, respondents face two scenarios with a total of 18 scenarios possible. In each scenario, respondents are shown the current fuel prices of gasoline and electricity as well as four alternatives in the vehicle choice set including the current vehicle, a new gasoline vehicle, a new hybrid vehicle, and a new electric vehicle. The characteristics of each alternative such as vehicle size, price, refueling range, and fuel economy change over time to mimic a dynamic marketplace. Respondents then choose either to keep their current vehicle or to buy a new one based on four instructions: (1) act as if you are actually buying a vehicle in a real life purchasing situation; (2) assume that you maintain your current living situation with moderate increase in income from year to year; (3) all prices are adjusted for inflation; and (4) each scenario is dependent on your previous choices. The survey collected 3598 observations of vehicle purchasing decisions from 456 Maryland households over the hypothetical nine-year period.

Before performing model estimation, we compared the descriptive statistics between the collected sample and the population in the Maryland area. The sampling method enforces a nearly even split between male and female respondents; however, the average education level of households in the sample is higher than in the population. In addition, the average number of adults and workers within households are slightly higher. The percentage of respondents who drive to work is slightly lower. The percentage of households with extremely high incomes ($250,000 or more) is also lower. Despite these differences, the patterns of household information between the sample and the population are quite similar, which suggests that the collected data can be representative for households in Maryland area.

Considering that household current vehicle characteristics will affect future vehicle purchasing decisions, we also analyzed the attributes of the vehicle fleet owned by the respondents. Compared to the population, the share of hybrid vehicle in the sample is slightly higher. Consequently, the average fuel economy (miles per gallon, MPG) is expected to be higher. Half of the vehicles are of medium size and the average number of vehicles within households is fewer than in the population. The sample underestimates the share of households in two extreme status – without vehicle and with three or more vehicles. Additionally, the data includes more vehicles that are less than three years old.

We also employed historical data from U.S. Energy Information Administration, including weekly gasoline prices from April 1993 to September 2015, and monthly electricity and gasoline prices from January 2003 to September 2015 in Maryland. The unit used for gasoline price is "dollars per gallon", while the unit for electricity price is transferred to "dollars per one-gallon-equivalent electricity". Although fluctuations are observed in fuel prices, there is a climbing trend for gasoline and electricity prices from 1993 to 2015, with two lower peaks around the year of 2009 and 2015.

5. Dynamic model estimation results

We estimate five different models to analyze households' preferences on new vehicle types and their characteristics in Maryland. The first model is a MNL, estimated for comparison purpose. The second one is the proposed dynamic structure with repeated purchases and no market evolution. The third model is the dynamic structure with repeated purchases and evolving gasoline price generated using an AR(1) process. The development of the forth model is based on the third one. It accounts for market evolution through the generation of gasoline and electricity prices with the VAR(1) process. The market evolution of the last model is the same as the forth model; however, we consider one-time purchases, which means households will be out-of-market immediately after their first purchase. The five estimation results are presented and compared in Table 1.

In each time period, respondents either keep their current vehicle or choose from three alternatives: a new gasoline vehicle, a new hybrid vehicle, and a new electric vehicle. Out of 500 respondents participated in the survey, 456 of them provided complete information and were included in the final sample for estimation. More importantly, although respondents are supposed to express their decisions for eighteen time periods over nine years, only the decisions from the first fifteen time periods are effective for the estimation, and decisions of the rest three are sacrificed for calculating the expected utility of the future. We find that the most appropriate look-forward time period is 3 by comparing the likelihood ratio index, the sign and t-value of estimated coefficients between models with look-forward time period equaling to 1, 2, 3, 4 and 5. In this case, the sample for estimation contains 3598 observations. The variables include vehicle price, size, fuel economy, refueling range, gasoline and electricity prices, number of vehicles held by a household, number of workers, and other social-demographic attributes.

5.1. MNL model results

All models are estimated on the same data set and with the same specification for consistency; results are shown in Table 1. We first estimate a MNL model for comparison purposes; the model is static; we ignore the panel effect and data is considered as cross-sectional; results are reported in the column "MNL". We can observe that the estimated coefficients have reasonable signs except for fuel economy of gasoline vehicle. Most coefficients are statistically significant except for the size and fuel economy of gasoline and hybrid vehicles, the range of electric vehicle, price of electricity, and the indicator of young people for the hybrid vehicle alternative. The coefficient related to the number of vehicles held by a household is positive, indicating that households with more cars are more likely to keep their current vehicles and to postpone the purchase of new vehicles. The coefficient associated with the number of workers is negative, which suggests that households with more workers tend to purchase new vehicles. As expected, the purchasing price coefficients are negative for all types of vehicles, and their magnitudes suggest that households are more sensitive to the price of electric vehicles, followed by gasoline vehicles, and least sensitive to the price of hybrid vehicles. Size coefficients are positive for all vehicle types attesting that households prefer large cars. On the other hand, the coefficients of fuel economy for hybrid and electric vehicles are positive, indicating that households prefer higher fuel efficiency. With reference to the operating cost, the magnitude of the estimated coefficients show that households are more sensitive to gasoline price. Besides, we find that female with a bachelor or higher degree are more likely to purchase hybrid vehicle, while young people or male with a bachelor or higher degree tend to buy electric vehicle.

5.2. Dynamic model results without market evolution

The dynamic structure captures the sequence of decisions made by a household over time; however, no market evaluation is considered and all attributes are static. The model specification remains the one adopted for the MNL case, and the estimation results are presented in the column "Dyn_R" of Table 1. We can observe that all coefficients are statistically significant. However, the sign of gasoline price and electricity price is incorrect. As already stated, gasoline price and electricity price are static variables generated from the scenarios presented in the SP survey. But the generated values from the SP survey might not necessarily reflect the values of

Table 1
Model estimation results: consumer's preference on vehicle type and characteristics.

Attributes [units]	Current	Gasoline	Hybrid	Electric	MNL estimate (t-stat)	Repeated purchases (Dyn_R) estimate (t-stat)	Repeated purchases (AR_R) estimate (t-stat)	Repeated purchases and (VAR_R) estimate (t-stat)	One-time purchase (VAR_S) estimate (t-stat)
Vehicles [number]	X				0.094 (2.0)	0.185 (15.8)	0.159 (15.5)	0.157 (13.8)	0.214 (11.9)
Workers [number]	X				−0.101 (−2.5)	−0.027 (−2.2)	−0.035 (−3.1)	−0.036 (−1.9)	−0.020 (−1.0)*
VehPrice.gas [$10,000]		X			−0.582 (−6.3)	−0.492 (−8.1)	−0.394 (−9.1)	−0.372 (−2.9)	−0.099 (−3.2)
size.gas [small, medium, large]		X			0.194 (1.5)*	0.905 (10.9)	0.344 (5.1)	0.333 (1.5)*	0.987 (6.0)
mpg_known.gas [100mpg]		X			−1.151 (−1.3)*^	10.111 (14.2)	7.682 (7.4)	7.394 (5.8)	14.570 (15.9)
mpg_unknown.gas [100mpg]		X			−1.619 (−1.8)^	8.631 (13.1)	0.485 (1.3)*	0.590 (1.2)*	13.782 (14.2)
GasPrice.gas [$1]		X			−0.270 (−3.4)	0.547 (7.5)^	−0.091 (−4.9)	−0.127 (−2.0)	−0.443 (−24.0)
ASC.hev			X		−2.263 (−4.6)	2.148 (4.5)	−1.053 (−9.3)	−0.927 (−1.0)*	2.071 (4.4)
D_Young.hev [1/0]			X		0.178 (1.6)*	0.489 (4.0)	0.377 (2.4)	0.314 (1.8)	0.524 (9.8)
D_EducFemale.hev [1/0]			X		0.218 (1.9)	0.434 (3.9)	0.158 (1.4)*	0.181 (1.2)*	0.169 (1.0)*
VehPrice.hev [$10,000]			X		−0.464 (−4.6)	−0.592 (−6.9)	−0.500 (−8.5)	−0.536 (−2.5)	−0.535 (−6.9)
size.hev [small, medium, large]			X		0.158 (1.4)*	0.706 (8.3)	0.408 (7.6)	0.382 (2.3)	0.372 (2.3)
mpg_known.hev [100mpg]			X		1.691 (2.5)	8.569 (14.3)	8.297 (6.8)	7.955 (4.9)	5.445 (3.3)
mpg_unknown.hev [100mpg]			X		0.803 (1.2)*	5.630 (10.1)	2.090 (11.6)	1.965 (1.7)	2.523 (1.8)
ASC.bev				X	−5.684 (−5.0)	−3.198 (−5.0)	−3.088 (−3.0)	−2.013 (−1.9)	4.385 (1.7)
D_Young.bev [1/0]				X	1.059 (6.3)	1.651 (9.9)	1.478 (8.5)	1.496 (8.2)	1.615 (5.7)
D_EducMale.bev [1/0]				X	0.396 (2.1)	0.739 (4.6)	0.497 (2.9)	0.436 (2.4)	0.350 (1.6)*
VehPrice.bev [$10,000]				X	−0.726 (−3.6)	−0.794 (−5.1)	−0.573 (−3.1)	−0.637 (−3.3)	−1.181 (−5.8)
size.bev [small, medium, large]				X	0.714 (3.3)	0.752 (4.6)	0.769 (3.8)	0.578 (2.7)	0.205 (0.4)*
range.bev [100miles]				X	0.544 (1.3)*	2.010 (5.6)	0.960 (2.5)	0.880 (2.1)	0.708 (1.1)*
mpg_known.bev [100mpg]				X	2.494 (3.7)	4.838 (9.8)	3.998 (6.5)	3.120 (4.4)	1.593 (0.7)*
mpg_unknown.bev [100mpg]				X	2.516 (3.8)	4.060 (8.4)	2.003 (3.2)	1.293 (1.9)	0.849 (0.4)*
ElePrice.bev [$1]				X	−0.107 (−0.6)*	0.123 (2.1)^	−0.327 (−2.0)	−0.321 (−1.8)	−0.557 (−2.2)
LL(0)					−5621.471	−8201.659	−8201.659	−8201.659	−5621.471
LL($\hat{\beta}$)					−3557.327	−2779.839	−2808.669	−2805.058	−1423.27
Likelihood ratio index					0.367	0.661	0.658	0.658	0.747

* Means the coefficient is not significant at significant level of 0.1.
^ Means the sign of the coefficient is not as expected.

fuel prices anticipated by the respondents. Compared to the MNL model results, the magnitude of coefficients related to the number of vehicles and number of workers indicates that households' purchase decisions are more sensitive to the number of vehicles and less sensitive to the number of workers in this dynamic structure. Different from MNL model results, the magnitudes of vehicle purchasing price coefficients suggest that households are more sensitive to electric vehicle price, then to the price of hybrid vehicles, and least sensitive to gasoline vehicle prices. This pattern seems to be more reasonable because households usually are reluctant to buy vehicles with new technologies, and a lower vehicle price will attract more buyers. The remaining coefficients of the dynamic model suggest that households prefer larger vehicle size, higher fuel economy, and longer refueling range.

5.3. Dynamic model results with market evolution

In this section, we present three DDCMs in addition to the specification presented in the previous Section, with the consideration of the dynamic evolution of fuel prices. In the first model only one attribute (gasoline price) is dynamic over the considered time horizon and repeated purchases are possible. For each SP scenario, gasoline price follows an auto-regressive model, and the residuals are standard normal distributed. The parameters of the AR model are calibrated using historical data; in particular we used gasoline prices from April 1993 to September 2015 (1169 observations total). The calibrated auto-regressive model presents the following specification:

$$y_{j,t+1} = 0.046458 + 0.98607 * y_{jt} + 0.05318 * \upsilon_{j,t+1}, \tag{19}$$

where $y_{j,t+1}$ and y_{jt} correspond to gasoline price (unit: \$/gallon) of adjacent time periods; and $\upsilon_{j,t+1}$ follows a standard normal distribution. From this formula, we observe that the auto-regressive factor is very close to one while the drift and standard deviation of the error are close to zero. The pattern indicates that gasoline prices have been relatively stable in the real market from 1993 to 2015. We use this formula to generate households' perspective dynamic gasoline price in each scenario for dynamic model estimation; the corresponding results are shown in the column named "AR_R" of Table 1.

All of the estimated coefficients are significant and have a reasonable sign except for fuel economy of gasoline vehicle and the indicator for educated female. Unlike the MNL model, the magnitudes of gasoline price and electricity price indicate that households are more sensitive to electricity price than to gasoline price. Another important observation is that the marginal effects of fuel economy are quite different between the two groups considered, those who know the fuel economy of their current vehicle and those who do not. Compared to the previous dynamic structure without market evolution, households are less sensitive to vehicle size and range. Although the magnitudes of the remaining coefficients slightly change, the signs and effects of these coefficients are consistent with the previous models.

The second and third dynamic models with market evolution are extensions of the first dynamic model presented and assume that gasoline price and electricity price vary simultaneously and dynamically over time; one allows repeated purchases and the other allows one-time purchase only. By assuming that gasoline price and electricity price for each SP scenario follow a vector auto-regressive model, we used monthly gasoline and electricity prices from January 2003 to September 2015 (153 observations totally) to calibrate the factors of the vector auto-regressive model. Drifts, and variance-covariance matrix of errors are determined under the hypothesis that the residuals follow a standard multivariate normal distribution. The final specification for the vector auto-regressive model is presented as follows:

$$\begin{bmatrix} y_{1,t+1} \\ y_{2,t+1} \end{bmatrix} = \begin{bmatrix} 0.071 \\ 0.529 \end{bmatrix} + \begin{bmatrix} 0.966 & -0.024 \\ 0.088 & 0.838 \end{bmatrix} \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} + \begin{bmatrix} 0.032 & -0.003 \\ -0.003 & 0.131 \end{bmatrix} \begin{bmatrix} \upsilon_{1,t+1} \\ \upsilon_{2,t+1} \end{bmatrix}, \tag{20}$$

where $\begin{bmatrix} y_{1,t+1} \\ y_{2,t+1} \end{bmatrix}$ and $\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}$ correspond to gasoline price (unit: \$/gallon) and electricity price (unit: \$/gallon-equivalent electricity) of adjacent time periods; and $\begin{bmatrix} \upsilon_{1,t+1} \\ \upsilon_{2,t+1} \end{bmatrix}$ follows a standard multivariate normal distribution. From this formula, we observe that the auto-regressive factor of electricity price is 0.838, smaller than that of gasoline price 0.966. The drift of gasoline price is very close to zero while that of electricity price is 0.529. The variance of the errors for gasoline price is close to zero while that of electricity price is 0.131. This pattern indicates that gasoline price is relatively stable in the market, while electricity price fluctuated from 2009 to 2015. We use this formula to generate households' perspective gasoline and electricity prices at each scenario. The dynamic models for repeated purchases or one-time purchase are estimated, and the corresponding results are shown in the column named "VAR_R" or "VAR_S" in Table 1.

When repeated purchases are considered, all coefficients have a reasonable sign and most of them are significant except for vehicle size, fuel economy of gasoline vehicle, and the indicator of educated female. Although small changes are observed, the estimation results of the dynamic structure considering two evolving variables are quite consistent with the one obtained considering one dynamic variable. In general, the fit of the model improves when we consider the dynamic nature of this problem; the rho-squared increases from 0.367 in the MNL model to 0.658 in the dynamic model with market evolution and repeated purchases.

When one-time purchase is considered, all coefficients have a reasonable sign. However, most of the households' social-demographic variables and the characteristics of electric vehicles are not significant. Obviously, this model is not appropriate to forecast households' vehicle purchase decisions based on the SP survey data available for this study. This is because in the survey we allow respondents to return to market and make another purchase every three years, which cannot be captured by the dynamic model with one-time purchase.

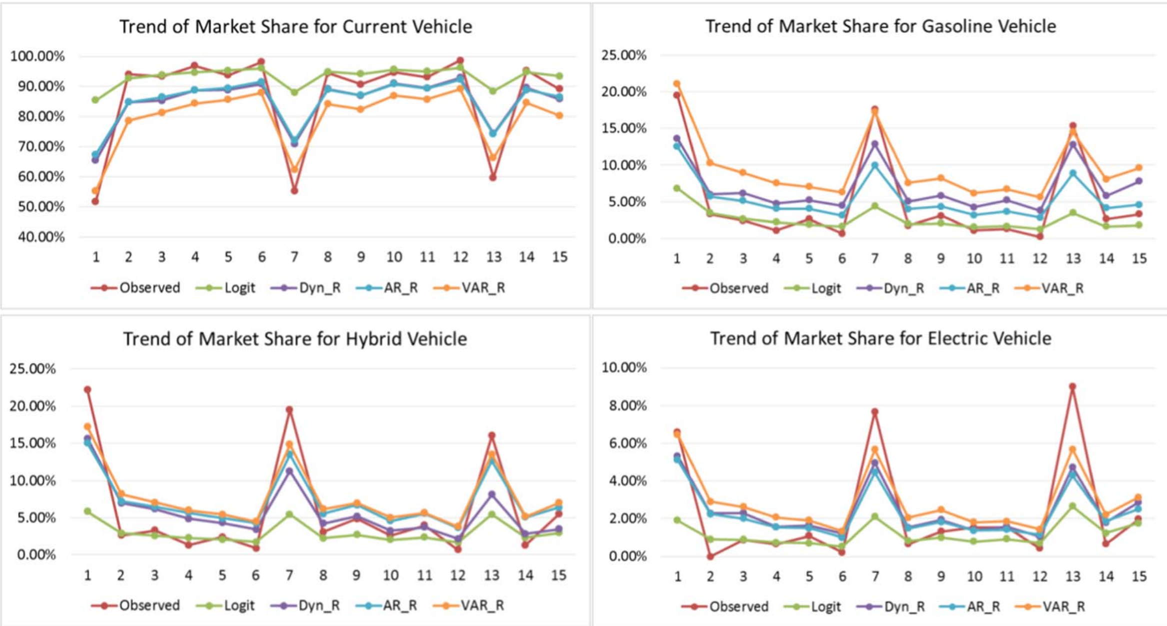

Fig. 1. Comparison of market prediction across static and dynamic models allowing repeated purchases.

5.4. Market share forecast

The estimated coefficients are used to predict the market share of different vehicle types, which measures the prediction power of both static and dynamic models allowing repeated purchases. Fig. 1 presents and compares the observed and predicted trends of market share of keeping the current vehicle, buying a new gasoline vehicle, a new hybrid vehicle, and a new electric vehicle along the 15 scenarios offered to the respondents over the nine-year period. In Fig. 1, the red line represents the observed market share; the green line is associated with the MNL model; the purple, blue, and orange lines are associated with dynamic model without market evolution, evolving gasoline price, and evolving gasoline and electricity prices, respectively. The probability of keeping the current vehicle is relatively high: it starts at 50% in the first scenario, it increases up to 90% for the following three years, then it returns to 55% in the seventh scenario, jumps to 90% again for the following three years, and goes down to 60% in the thirteenth scenario. New gasoline, hybrid, and electric vehicles occupy smaller market shares: starting at 20%, 23%, and 7% respectively in the first scenario, they decrease to less than 5%, and then go up again in the third year. The big fluctuations in our data are due to the survey design; respondents who purchase a new vehicle are assumed to be out-of-market for the following three years and during this time period they are restricted to keep their current vehicles. By observing the peak values over the 15 scenarios, the market shares of keeping the current vehicle and buying an electric vehicle slightly increase from 50% to 60%, and from 7% to 9% respectively. On the other hand, the market shares of choosing new gasoline and hybrid vehicles decreases from 20% to 15%, and from 23% to 16% respectively during the same period.

From Fig. 1, we observe that the static MNL model predicts a very stable market share and it is incapable to capture fluctuations and peaks of the market share. More specifically, it predicts well only the upper bounds of market share of keeping the current vehicle and the lower bounds of buying new gasoline, hybrid, and electric vehicles respectively. All three dynamic models are able to recover the fluctuations of the real market share, especially the model with evolving gasoline and electricity prices that approximates all the peaks over the 15 scenarios. However, the dynamic models underestimate the upper bound of market share of keeping the current vehicle, and overestimate the market share lower bound of buying new gasoline, hybrid, and electric vehicles. To summarize, the dynamic models are excellent to predict fluctuations and peaks in market shares while the MNL model averages market shares over time and fails to detect sudden changes in consumer demands.

Fig. 2 compares the prediction power of two dynamic models with evolving gasoline and electricity prices: the blue line allows repeated purchases and the green line allows one-time purchase. We observe that the one-time purchase model averages the market shares over time and is incapable of predicting fluctuations, peaks, upper bounds and lower bounds in the real market share. On the other hand, the model allowing repeated purchases does an excellent job in predicting fluctuations and peaks of the actual market share.

6. Model validation and sensitivity analysis

In order to validate the model results, we re-estimated both static and dynamic models on 80% of the sample and applied the model estimates to the remaining 20% of the sample. Fig. 3 reports the Root Mean Square Error (RMSE) of market shares calculated

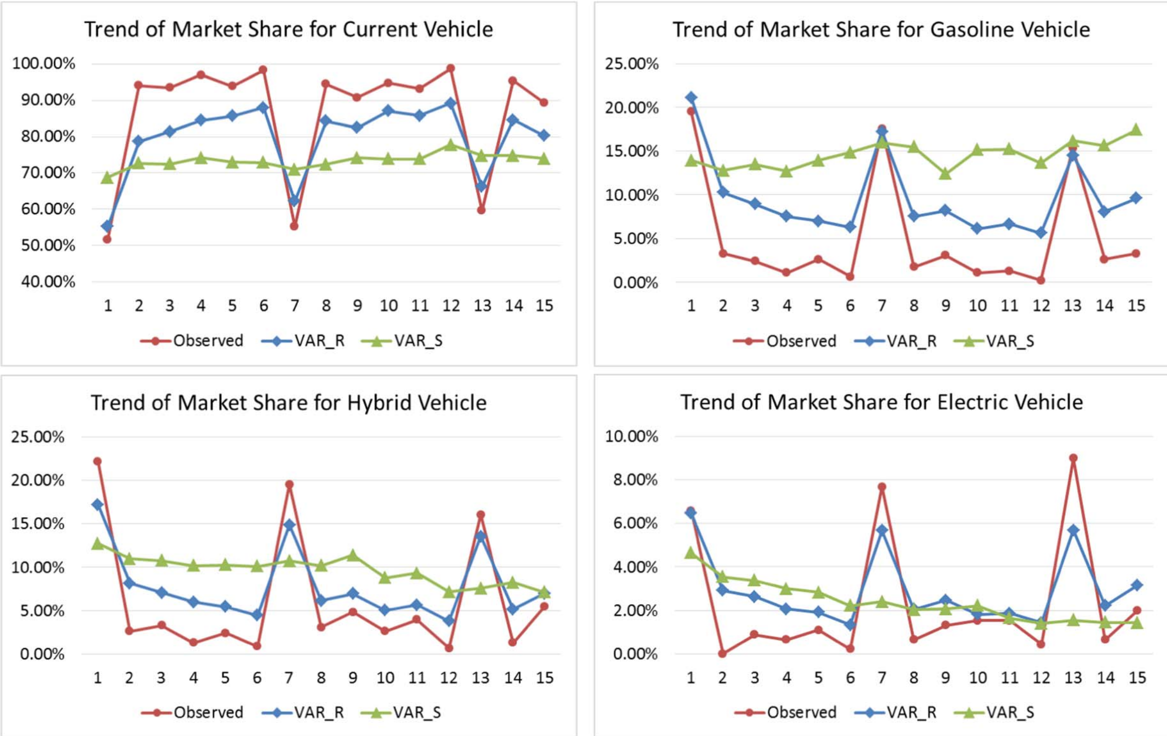

Fig. 2. Comparison of market share prediction across dynamic models allowing repeated purchases and one-time purchase.

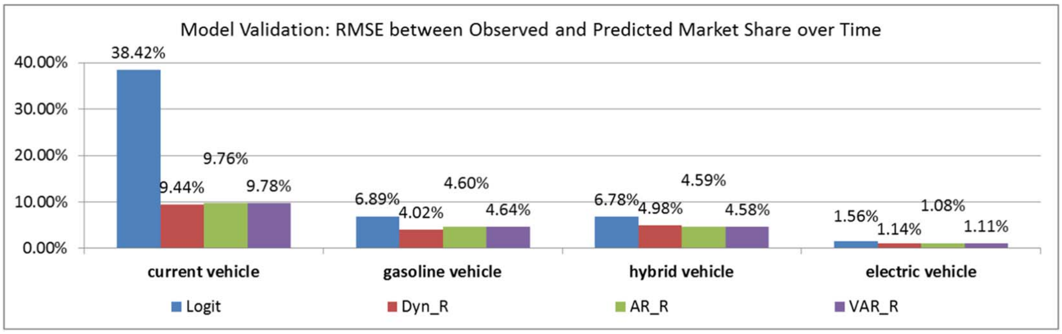

Fig. 3. Model validation results: RMSE between observed and predicted vehicle market share over time.

respectively for the static logit model and the three dynamic models over the fifteen time periods considered. The RMSE values suggest that the logit model has the highest prediction error, especially in reproducing the market share of the current vehicle; while in comparison the dynamic models performs equally well.

The estimation results of the dynamic model with evolving gasoline price and electricity price have been applied to test policy scenarios; the variables of interest are fuel price (i.e., gasoline price and electricity price), vehicle purchase price (i.e., hybrid vehicle price and electric vehicle price), and characteristics of electric cars (i.e., MPG equivalent electricity and recharging range). More specifically, the scenarios investigated are as follows:

- Fuel price
  Gasoline price over 15 time periods: 10% decrease, 10% increase
  Electricity price over 15 time periods: 10% decrease, 10% increase
- Vehicle purchase price
  Price of hybrid car over 15 time periods: 10% decrease, 10% increase
  Price of electric car over 15 time periods: 10% decrease, 10% increase
- Technology improvement
  MPG equivalent electricity over 15 time periods: 10% decrease, 10% increase
  Recharging range of electric car over 15 time periods: 10% decrease, 10% increase

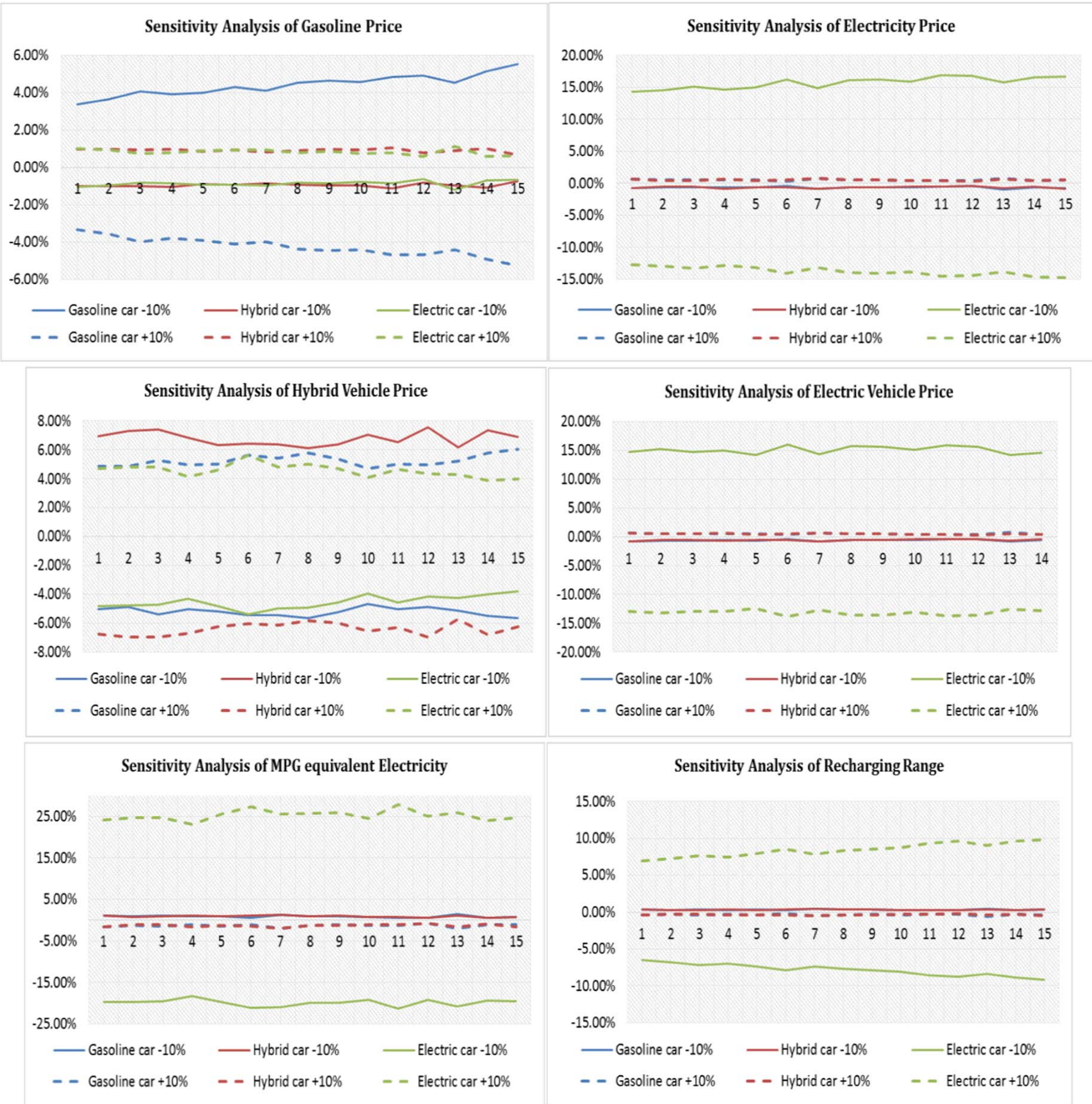

Fig. 4. Application results of dynamic models with two evolving attributes: sensitivity analysis of fuel price, vehicle price, and electric car characteristics. *Note: The above six pictures describe the changes in the market share of gasoline, hybrid and electric cars when the target variables increase or decrease by 10%. For example, in the first picture, "Gasoline car −10%" or "Gasoline car +10%" means the change in the market share of gasoline car when gasoline price decreases or increases by 10%.*

Results in Fig. 4 show how the changes of these variables influence households' decisions of purchasing gasoline, hybrid, or electric cars over time at an aggregate level. Overall, the impact of all tested variables on vehicle type decisions is significant. Changes in fuel price have a large effect on the purchase of the corresponding vehicle type, especially the changes of electricity price on the purchase of electric cars. We observe that the effect of gasoline-price changes on gasoline-vehicle purchase gradually increases over the 15 time periods, while it is not obvious to identify a trend for the change of electricity price.

Changes in vehicle price also have a large effect on vehicle type choices. The effects have different patterns under the changes of hybrid and electric vehicle prices. The decrease/increase of hybrid vehicle price encourages/discourages households to buy hybrid cars, while discourages/encourages them to buy gasoline and electric cars. For example, at time period 1, a 10% decrease in the price of hybrid car leads to a 7% increase in the purchase of hybrid car and a 5% decrease in the purchases of gasoline and electric cars. We observe that the impact of hybrid vehicle price on vehicle type choices fluctuates over time. The changes in the price of electric car only influence the choice of electric car, and the effects on gasoline and hybrid cars are negligible. For example, a 10% increase in electric vehicle price leads to a 13–14% decrease in the purchase of electric car, and less than 1% increase in the purchase of other vehicle types. We observe little variation in the effect of electric vehicle price on vehicle type choices over time.

Additionally, we test some variables related to the technology improvement of electric car, such as MPG equivalent electricity and

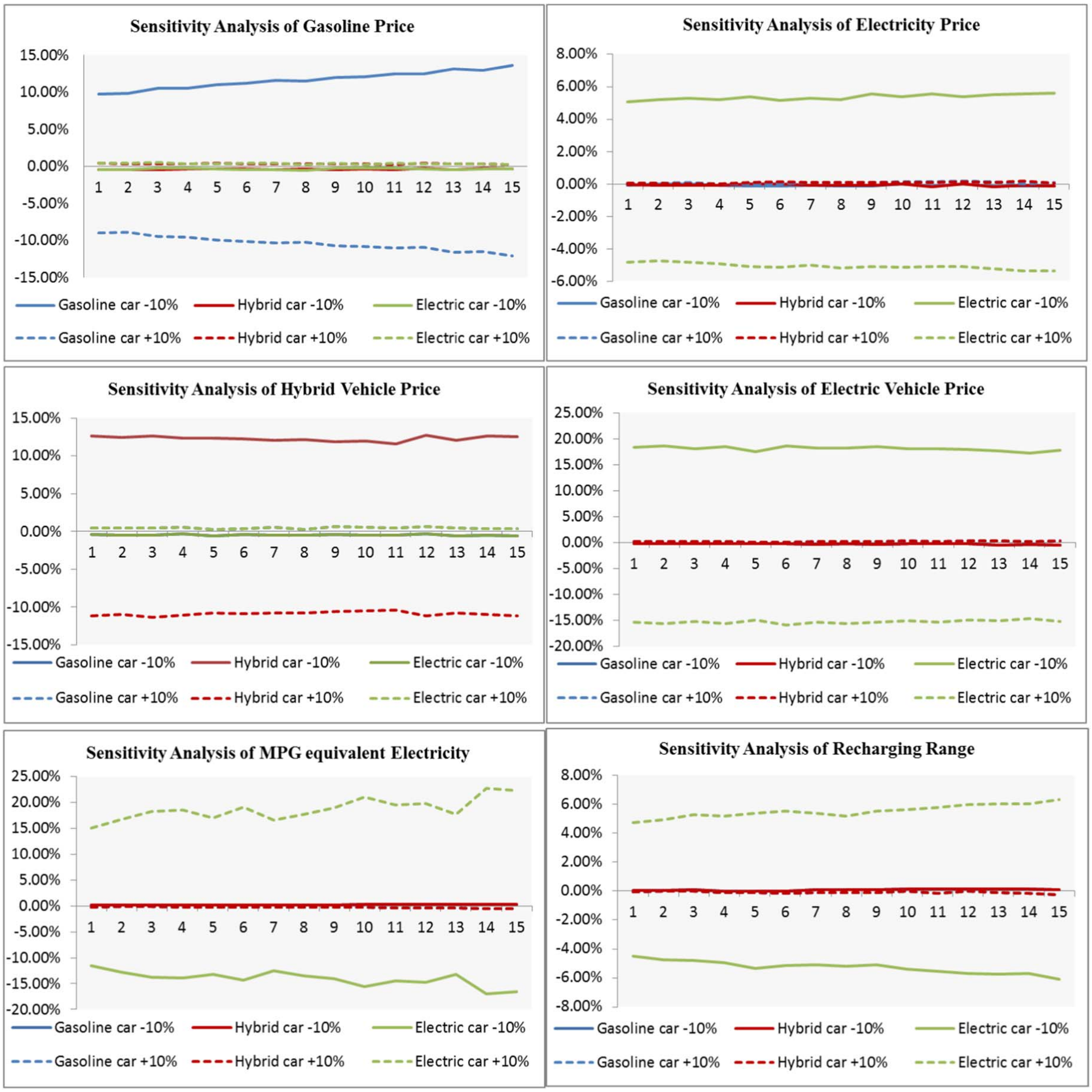

Fig. 5. Application results of logit model: sensitivity analysis on fuel price, vehicle price, and electric car characteristics.

recharging range. We observe that the purchase of electric car is very sensitive to the change of car characteristic variables, especially MPG equivalent electricity. To summarize, compared to the purchase of gasoline and hybrid cars, the purchase of electric car is more sensitive to the change of fuel price, vehicle price, and car characteristics.

Finally, we test the same policy scenarios using the logit model estimates; the impacts on household's vehicle type choices over time are reported in Fig. 5. Regarding the impact of changes in fuel price on vehicle type choices, the logit model overestimates the impact from changes in gasoline price and underestimates that for electricity price. This result indicates that the potential users are more sensitive to the change of gasoline price than electricity price, which is not coherent with general expectations.

In contrast to the dynamic model results, we observe that the impacts caused by changes in vehicle prices are very stable and have little variation over time. The changes in the price of hybrid/electric cars only influence the purchase of the corresponding vehicle types (hybrid/electric cars), and the impact on the choices of other vehicle types are negligible. For example, a 10% increase in hybrid (electric) vehicle price leads to a 11–12% (15–16%) decrease in the purchase of hybrid (electric) cars, and less than 1% (0.5%) increase in the purchase of other vehicle types. Additionally, when increasing the price of hybrid (electric) cars, logit model is not able to predict the difference between the impact on the purchases of other vehicle types including gasoline cars and electric (hybrid) cars. A similar pattern is found when testing scenarios with improved fuel economy and recharging range of electric vehicles.

7. Conclusions

This paper formalizes a general dynamic discrete choice framework in which forward-looking agents optimize their utility over time; two options are available at each time: keeping the current vehicle or buying a new vehicle among the options available in the market. Different model forms are proposed to consider the purchase pattern of different durable goods in the market: a regenerative formulation allows agents to return to the market after a purchase is made, while a one-time purchase formulation assumes that agents are out of the market after a change in status. The model accounts for dynamically evolving market conditions by a stochastic diffusion process, either an auto-regressive process or a vector auto-regressive process, that models time series correlations of a single or multiple correlated variables.

The proposed model frameworks have been successfully applied to predict preferences among different vehicle types that include new gasoline, hybrid, and electric vehicles. Model estimates are coherent with general expectations. In particular, the basic dynamic model correctly recovers the MPG coefficients, while the dynamic models with evolving market variables (simulated by AR1 or VAR1) produce negative marginal utility for fuel price including gasoline price and electricity price.

Generally, the DDCMs dramatically improve the model fit with respect to the MNL model. Model validation shows that dynamic models are particularly appropriate to recover peaks and rapid changes in consumer demand over time. On average, the dynamic models have a better performance in predicting the vehicle market share.

Concerning the behavior derived from the analysis, it is possible to conclude that consumers are more interested in purchasing gasoline and hybrid cars, for which the predicted market shares peak around 20% over the nine-year study period. Electric cars represent 4–7% of the future market and there is a slightly increasing trend over time. The market share of electric car highly depends on electricity price, purchasing price of electric car, MPG equivalent electricity, and recharging range.

To conclude, the DDCMs are appropriately implemented and applied to model preferences towards green vehicles. In order to further assess their potential, more case studies are necessary. Applications on revealed preference panel data will help analysts to test the ability of the DDCMs to recover market shares over time in real market conditions. Moreover, the dynamic modeling frameworks proposed can be further extended to account for consumer's taste heterogeneity, flexible correlation patterns, and panel effect.

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