

**Alternative Modeling Approaches Used for Examining Automobile Ownership: A  
Comprehensive Review**

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## **ABSTRACT**

Household vehicle ownership and the associated dimensions including fleet size, vehicle type and usage has been one of the most researched transport topics. This paper endeavours to provide a critical overview of the wide ranging methodological approaches employed in vehicle ownership modeling depending on the ownership representation over the past two decades. The studies in the existing literature based on the vehicle ownership representation are classified as: exogenous static, exogenous dynamic, endogenous static and endogenous dynamic models. The methodological approaches applied to range from simple linear regressions to complex econometrics formulations taking into account a rich set of covariates. In spite of the steady advancement and impressive evolution in terms of methodological approaches to examine the decision process, we identify complex issues that pose a formidable challenge to address the evolution of vehicle ownership in the coming years. Specifically, we discuss challenges with data availability and methodological framework selection. In light of these discussions, we provide a decision matrix for aiding researchers/practitioners in determining appropriate model frameworks for conducting vehicle ownership analysis.

## 1. Introduction

Private car ownership (fleet size and composition) plays a vital and ubiquitous role in the daily travel decisions of individuals and households influencing a range of long-term and short-term decisions. In the long-term, the vehicle ownership decisions are strongly tied with residential location and residential tenure (Bhat and Guo, 2007; Eluru *et al.*, 2010a; Paleti *et al.*, 2013b). In the short-term, car ownership affects the various aspects of activity travel patterns including activity frequency, activity duration, activity location (and thus associated mileage), and travel mode choice for out-of-home work and non-work pursuits (Bunch, 2000, Eluru *et al.*, 2010b).

The adverse impacts of over reliance on private automobiles for personal travel are well documented in literature. Given the wide ranging implications, household vehicle ownership and the associated dimensions including fleet size, vehicle type and usage has been a topic of great interest to policy makers. Historically, models to investigate car ownership and usage have been under development since the 1930's (Whelan, 2007). The earlier literature has been focussed on examining car ownership at an aggregate level (Holtzclaw *et al.*, 2002; Clark, 2007). These studies analyse the ownership decision process at the national, regional or zonal level. The approach fails to capture the underlying behavioural mechanisms that actually guide the household decision process. Thus, their accuracy and policy sensitivity in practical applications is very limited (Kitamura and Bunch, 1990). On the other hand, disaggregate models, in which the "unit of observation" are individual households, alleviate many of these difficulties and can lead to more precise, detailed and policy relevant model findings (Eluru and Bhat, 2007). Therefore, more recent studies have focussed on examining the car ownership decision at a disaggregate level (household level). We will focus on such household-level studies. The methodological approaches applied to model car ownership range from simple linear regression to complex econometric formulations taking into account a rich set of covariates (Brownstone and Golob, 2009). The choice of model structure and functional form are typically driven by the objectives and context of the study. It is in this context that we undertake our review to examine the various methodological approaches employed in vehicle ownership modeling depending on the vehicle ownership representation.

### Vehicle Ownership Representation

The dimension of crucial interest in vehicle ownership analysis is how to represent the ownership in the decision process. The methodological framework and policy analysis components are heavily reliant on the characterization of this decision process. In the extant transport and travel behaviour literature, several representations of the automobile demand of households have been employed. In fact, the vehicle ownership representation provides us a clear framework for classifying the various research efforts examining vehicle ownership decision processes as highlighted in the subsequent discussion.

The simplest of the vehicle representation decision processes is the decision of how many vehicles to own or "auto ownership level" at a particular point of time (for example, see Manski and Sherman, 1980; Bhat and Pulugurta, 1998; Potoglou and Susilo, 2008). With the growing emphasis on vehicular emission modeling, there has been considerable work on modeling household fleet composition in terms of the mix of vehicle types (such as sedan, van, pick-up

truck, Sports Utility Vehicle (SUV)) owned by a household (for example, see Mohammadian and Miller, 2003b; Choo and Mokhtarian, 2004). This group of studies are referred to as *exogenous static models* in our review i.e. studies that treat vehicle ownership as independent of other decisions.

Another line of inquiry is focussed on examining the influence of one component of vehicle ownership on another component of vehicle ownership. For instance, it is plausible that individuals that have unobserved inclination for purchasing a pick-up truck are likely to have a positively influencing unobserved component for accumulating mileage with it. In fact, there is growing evidence to indicate that unobserved factors (e.g. proclivity towards a particular vehicle, perception of comfort, environmental consciousness) that influence household's vehicle type purchasing decisions also impact the usage decisions for that vehicle. The examination of vehicle ownership models also reveals significant influence of land use and urban form on the vehicle fleet decision process (Schimek, 1996; Yamamoto, 2009; Zegras, 2010). However, recent studies have demonstrated that incorporating land use and built environment as mere exogenous variables is not accurate as households have inherent preferences for residential location decisions thus leading to self-selection (Pinjari *et al.*, 2008; Pinjari *et al.*, 2011). There have been research efforts that attempt to capture the influence of other decision processes on vehicle ownership decisions. The process of accommodating for influence of additional dimensions is along the same lines of accounting for influence of unobserved components in the joint modeling of various components of vehicle ownership. In our review, these set of studies are together referred to as the *endogenous static models*.

The vehicle ownership representations discussed above are based on a snapshot of the vehicle ownership profiles - *static*. However, behaviorally households pass through a vehicle fleet decision process over time that includes vehicle purchase and vehicle disposal/sale. The changes to household vehicle fleet might be triggered by many events such as the birth of a child, changes to marital status affecting the vehicular requirements of the household. Naturally, research efforts have examined these decisions through a whole suite of models - vehicle holding duration, acquisition, disposal, and replacement models (Gilbert, 1992; Yamamoto *et al.*, 1999). These studies consider the evolution of vehicle fleet i.e. they are not focussed on the snapshot, but examine each vehicle fleet change decisions. This analysis allows analysts to see how life cycle changes in a household and existing fleet influence vehicle ownership decisions. These studies could examine vehicle ownership as a number or the more refined vehicle type characterization. The reader would recognize that all the vehicle ownership representations that consider vehicle ownership as a snapshot can be re-analyzed within this evolution framework giving rise to *exogenous dynamic models* and *endogenous dynamic models*.

## Current Study

The primary objective of our research is to provide a systematic overview and assessment of the methodological alternatives in the context of various potential representations of the vehicle ownership decision process. To be sure, there have been earlier efforts to review the progress in modelling the vehicle ownership decision process (see de Jong *et al.*, 2004; Potoglou and Kanaroglou, 2008a; Bunch, 2000). The last two studies focus on a small sample of methodological frameworks in their review. de Jong *et al.* (2004) provides a very comprehensive

review of vehicle ownership models developed for the public sector. The study discusses both aggregate and disaggregate models developed prior to 2002. In recent years, owing to advances in computing, many advanced frameworks are being applied to model vehicle ownership. We review these recently developed modeling approaches and document their application in the context of the vehicle ownership representation discussed above. To summarize, the models found in the existing literature are classified as follows:

- The exogenous static models predict vehicle holdings at a particular instance in time ignoring the dynamics of vehicle evolution.
- Endogenous static models jointly model vehicle ownership with other decision processes considering that one choice dimension (such as vehicle ownership or vehicle type) is not simply an exogenous factor (e.g. vehicle usage), but is endogenous to the system.
- The exogenous dynamic models examine evolution in vehicle ownership decisions.
- The category of endogenous dynamic models consists of models in which both endogeneity between household fleet size or composition or usage decisions and dynamics associated with the vehicle acquisition process are considered.

## 2. Methods

A summary of earlier studies (since 1990) classified based on the four vehicle ownership representations identified above is provided in Table 1. The table provides information on the study, data source, modeling methodology, vehicle demand form, what variables are considered including household demographics, individual, employment and life cycle attributes, built environment characteristics, transit attributes, policy scenarios and unobserved effects. Several observations could be made from the table. *First*, most vehicle ownership studies are from North America (50 out of the 83 studies are from US and Canada). One quarter of the studies (22) is based on European data and a small number of studies are in the Asian (10), Australian (2) and South American (1) contexts. *Second*, for model estimation, the majority of studies (64 out of 83) rely on cross-sectional travel behaviour surveys. *Third*, vehicle ownership decision has been mostly investigated as static exogenous choice using unordered choice mechanism with the most prevalent model structure being the multinomial logit (MNL). *Fourth*, household demographics and built environment characteristics (land use, urban form, and street network attributes) are the two most commonly examined exogenous variable groups. In recent years, the impact of transit attributes on the ownership decision process has also been investigated (32 out of 83)<sup>1</sup>.

### Exogenous Static Models

Within this group of models, the vehicle ownership decision process is considered in isolation of other choices. Based on the modeling approach employed, we have further sub-categorized the exogenous static models into standard discrete choice models, count models, advance discrete choice models and other approaches.

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<sup>1</sup> For our literature review, we primarily focused on travel behavior literature while augmenting with research from marketing literature. The review process involved a two pronged approach. First, we employed the standard research databases for literature search on vehicle ownership. Second, a comprehensive cascading search of research based on the references in highly cited research articles on vehicle ownership was conducted. The two approaches ensured we covered the broad spectrum of literature on vehicle ownership.

### *Standard discrete choice models*

Researchers have most commonly applied binary logit regression to represent binary car ownership levels of households, such as, owning a car vs. not owning a car. These models capture the household's trade-off between the benefits (safety, privacy) of owning a private vehicle and disadvantages (higher travel time) of not owning it (Karlaftis and Golias, 2002; Li *et al.*, 2010; Ma and Srinivasan, 2010). However, they do not distinguish the number of vehicles owned by households.

The issue of captive or loyal decision-making units (individual households) is another important aspect of car ownership modeling. In many instances, households, for one reason or another (financial constraints or environmental consciousness), will never own a car. If this captivity or loyalty to a particular choice alternative is not taken into account during model calibration, it can lead to biased estimation of coefficients (Swait and Ben-Akiva, 1986). To handle this problem, Gaudry and Dagenias (1979) proposed the dogit model, which considers choice set composition rather than considering a universal choice set. Specifically, it allows for two choice sets – (1) choice set with just the chosen alternative and (2) choice set involving all alternatives. Of course, the dogit model forms a special case of full latent choice set consideration approach (Basar and Bhat, 2004). Whelan (2007) applied hierarchical binary dogit model by introducing a market saturation term for each level of household car ownership which would account for the range of reasons why some households are unable to acquire a vehicle or add to their existing stock.

Household vehicle ownership variable is often compiled in travel surveys as an ordinal discrete variable. Naturally, many approaches exploit the inherent ordering of the discrete variable by employing ordered response models (ORMs). The most commonly used ORMs in the representation of auto ownership are the traditional ordered logit (OL) (see Potoglou and Susilo, 2008; Potoglou and Kanaroglou, 2008b) and probit (OP) (see Potoglou and Susilo, 2008; Ma and Srinivasan, 2010) models. These models are derived from a latent variable framework where a single continuous latent variable reflects the propensity of a household to own vehicles. The latent variable cannot be measured directly, but is mapped to the observed vehicle ownership levels.

The unordered multinomial discrete outcome models do not explicitly take into account the ordinal nature of the observed levels of car ownership. Rather, the mechanism is based on the random utility maximization (RUM) principle. Decision making units (households) associate a certain level of utility with each car ownership level/type and choose the level/type that yields the maximum utility (see Potoglou, 2008; Zegras, 2010; Caulfield, 2012; Wong, 2013). The most common model arising from the RUM framework is the multinomial logit (MNL) model. Besides its closed form solution and computational simplicity, the standard MNL also has the advantage of increased flexibility in model specification. That is, unlike OL or OP models, the MNL model does not place any restrictions on the effect of household characteristics across car ownership levels (Savolainen *et al.*, 2011). The additional flexibility, however, results in the estimation of substantially more parameters (Washington *et al.*, 2011). Moreover, the traditional MNL model is also susceptible to the violation of independence of irrelevant alternatives (IIA) property.

In case the IIA property is not likely to be valid, the nested logit (NL) model structure has been suggested as an appropriate generalization of the MNL model. This model allows for correlation between the utilities of alternatives in common nests (Koppelman and Sethi, 2008). In order to estimate the model, car ownership levels or vehicle types that are presumably similar to each other (due to unobserved preferences) are grouped into nests (see Mohammadian and Miller, 2003b; Cao *et al.*, 2006; Guo, 2013). For instance, vehicle fleet decision can be partitioned into two levels, with vehicle availability (owning zero car vs owning car) being the first level while owning one car and owning two or more cars forming the second level and a two level NL model can be estimated (Kermanshah and Ghazi, 2001). In the context of vehicle type choice, McCarthy and Tay (1998) argued that vehicle makes/models can be nested according to their fuel efficiency, i.e. make/models in each fuel efficiency nest have similar unobserved characteristics and, accordingly, are likely to be correlated. Hence, they estimated a two level NL model for new vehicle purchase choices, where the first level contained three branches (low, medium and high fuel efficiency), and the second level contained all make-model combinations in the respective fuel efficiency category. Again, another possible correlation across alternatives is the correlation with adjacent alternatives – i.e. owning 2 cars is closely related to owning 1 car and 3 cars; an ordered generalized extreme value (OGEV) model (Small, 1994) can accommodate such structures. The assignment of alternatives to positions in the nesting structure and the number of nesting levels is the prerogative of the analyst. However, the NL model retains the restrictions that alternatives in a common nest have equal cross-elasticities and alternatives not in a common nest have cross-elasticities as for the MNL (Koppelman and Sethi, 2008).

### *Count models*

The observed automobile ownership levels of household are non-negative integers. Recognizing this property, several researchers have applied count data regression models to model car ownership data. However, the application of count data regression models for modeling car ownership is not quite common.

The standard Poisson regression model assumes that the number of automobiles owned by household is independently Poisson distributed (see Shay and Khattak, 2011). The standard Poisson model is based on the equal-dispersion assumption that the mean is equal to the variance. The assumption, however, is very restrictive because it does not hold in many cases, particularly when there is over or under-dispersion in the data. For instance, assuming a Poisson distribution for auto ownership data with problems of over-dispersion would result in underestimation of the standard error of the regression coefficients, which can lead to a biased selection of covariates. Moreover, the efficiency of the estimated parameters is also lost (Karlaftis and Golias, 2002).

The most extensively used approach to address the problem of inequality of mean and variance of the process is the negative binomial (Poisson-gamma) regression model. Unlike Poisson model, the mean car ownership level is assumed to be random following a gamma probability distribution in the negative binomial model (see Shay and Khattak, 2005; Shay and Khattak, 2007). When the overdispersion parameter is equal to zero, the negative binomial model reduces to Poisson regression model. The model has a closed-form solution; however, it is criticized by researchers for its incapability of handling under-dispersed data (Lord and Mannering, 2010).

In the car ownership literature, researchers have also used another modified version of the Poisson model termed as the Poisson-lognormal model (see Karlaftis and Golias, 2002). In this model, the error term is assumed to be log-normal-rather than gamma-distributed. The model can account for unobserved heterogeneity and is more flexible than the negative binomial model (it can be easily extended to the multivariate setting). However, one important limitation of the model is that the marginal distribution of the model does not have a closed form expression as the Poisson-gamma model (Winkelmann, 2008).

The application of count models for household car ownership is quite restrictive because the household ownership variable rarely has values higher than 3 – thus allocating non-zero probability for a huge number of alternatives that are unlikely to be feasible for a large proportion of the population. Ideally, ordered response models are better suited to modeling vehicle ownership compared to the count models. In fact, in a recent paper (Castro *et al.*, 2012) the authors' show that count models can be appropriately recast as ordered response models, providing further evidence that ordered models are more appropriate when the universal choice set is comprised of small number of categories.

#### *Advance discrete choice models*

The traditional discrete choice models impose the restriction that the model parameters are same for the entire population – population homogeneity assumption. However, it is possible that the exogenous variable effects might vary across the population. Endogenous segmentation is an elegant approach for accommodating such systematic heterogeneity. The modeling technique has several appealing advantages. First, each segment is allowed to be identified with a multivariate set of exogenous variables, while also limiting the total number of segments to a number that is much lower than what would be implied by a full combinatorial scheme of the multivariate set of exogenous variables. Second, the probabilistic assignment of households to segments explicitly acknowledges the role played by unobserved factors in moderating the impact of observed exogenous variables. Third, within each segment, separate vehicle ownership representations can be estimated (unordered/ordered) to examine household choice behavior (see Anowar *et al.*, 2014a; Beck *et al.*, 2013). Finally, it circumvents the need to specify a distributional assumption for the coefficients (Greene and Hensher, 2003). Anowar *et al.* (2014a) estimated latent segmentation based ordered logit (LSOL) and latent segmentation based multinomial logit (LSMNL) models of car ownership. The authors found that there are two distinct population segments with respect to vehicle ownership. The probability of belonging to any segment was a function of land use characteristics and household demographics. Based on the segment specific car ownership shares and variable means within the segment, they characterized segment 1 as transit independent (TI) and segment 2 as transit friendly (TF). It is important to note that latent class models are prone to stability issues in the estimation process. Such issues can be overcome by coding the log-likelihood function and its corresponding gradient function.

#### *Other approaches*

In recent years, machine-learning techniques such as neural network or genetic algorithm (GA) are being applied to traffic and transportation problems. Mohammadian and Miller (2002) applied multilayer perceptron artificial neural network (ANN) for predicting household auto



choices and also compared the results with the outcomes of traditional discrete choice method – the NL model. Typically, a neural network structure consists of a series of nodes. These are: input nodes for receiving the input signals, output nodes for giving the output signals, and hidden or intermediate nodes. Also, there are weight factors that link the various nodes together in hierarchical manner and these are assumed to be fixed in ANN (Lord and Mannering, 2010). This technique is capable of identifying associations among different variables in the database in a much quicker time than the traditional discrete choice models. However, their application for policy and sensitivity is very limited due to lack of explicit sensitivity measures (Mohammadian and Miller, 2002).

### *Synopsis*

It was evident from the review that standard discrete choice models are by far the most commonly employed modeling approach. Majority of the studies either applied the ordered or the unordered response mechanism. However, two of these studies attempted to compare the performance of the ordered and unordered response structures (Bhat and Pulugurta, 1998; Potoglou and Susilo, 2008). Based on several measures of data fit, these studies concluded that unordered response mechanisms such as MNL are more appropriate for auto ownership modeling. Further, advanced models such as the latent segmentation models are found to outperform their traditional counterparts in Anowar *et al.* (2014a). They are also theoretically superior because they can accommodate systematic heterogeneity and thus allow for enhanced policy analysis.

### Endogenous Static Models

In this section, we consider approaches that allow for modeling vehicle ownership in conjunction with other household choice outcomes. The joint modeling of multiple choices presents various methodological challenges. Broadly, two methods are employed to undertake such analysis. In the *first approach*, standard discrete choice methods described earlier are employed to analyze joint choices by defining choice alternatives as combination of various choices (such as residential location and vehicle ownership levels). The *second approach*, considers methods that incorporate unobserved correlations/dependencies across choice processes. The actual form of the model developed is based on the mechanism employed to accommodate these correlations. Based on these two approaches, the range of models applied in the context of vehicle ownership include: standard discrete choice models, mixed multidimensional choice modeling techniques, discrete continuous models, copula based models, Bayesian models, simultaneous equation models and structural equation models (SEM).

### *Standard discrete choice models*

Standard discrete choice econometric frameworks are also used to simultaneously model auto ownership choice with other decision processes of households, such as, mode choice, trip chaining or residential location. More specifically, in this type of modeling, all choice dimensions are considered as endogenous and are modelled as single joint choice (theoretically consistent with the joint utility maximization). For instance, Dissanayake and Morikawa (2002) developed a two level NL model to analyze vehicle ownership, mode choice, and trip chaining

behaviours of households in Bangkok metropolitan region, Thailand. Salon (2009) applied the traditional MNL model for investigating the choices of car ownership and commute mode along with the choice of residential location of households in New York City.

Weinberger and Goetzke (2010) applied multinomial probit (MNP) model to jointly analyze the automobile ownership/residential location while capturing the effect of person's previous observations and experiences on the decision process. MNP model can also be derived following the random utility theory with the disturbance term assumed to be multivariate normally distributed. It allows for the relaxation of the IIA assumption, thus ensuring unbiased coefficient estimates despite possible correlation among different car ownership levels (Weinberger and Goetzke, 2010). However, the outcome probabilities are not closed form and hence, the estimation of the likelihood function requires numerical integration of multi-dimensional integrals making the model computationally difficult and time consuming (Washington *et al.*, 2011)<sup>2</sup>. Again, it has to be recognized that combining choice alternatives of multiple choice dimensions into one compound choice bundle can lead to a dramatic increase in the number of choices to be modelled. Moreover, none of the approaches can be used when the travel attribute is continuous (Pinjari *et al.*, 2011).

#### *Mixed multidimensional choice modeling*

In the unified mixed multidimensional choice modeling approach, various decision processes (continuous, ordinal, multinomial and count) are jointly modelled by formulating a series of sub-models for different choice dimensions. For example, Bhat and Guo (2007) developed an MNL model of residential location and an OL model of vehicle ownership to account for the residential self-selection effects. In another study, Pinjari *et al.* (2011) extended this approach and consequently developed an MNL model of residential location, OL models of vehicle ownership and bicycle ownership, and an MNL model of commute mode choice. Very recently, Paleti *et al.* (2013c) used the MNP model in order to jointly model residential location choice and vehicle ownership choice process while controlling for the immigration status of residents. Within the choice continuum, the sub-model components are econometrically joined together by using common stochastic terms (or random coefficients, or error components) and the parameters for each choice dimension are estimated simultaneously. The modeling framework is capable of incorporating a multitude of interdependencies among the choice dimensions of interest, such as: self-selection and endogeneity effects, correlation of error structures and also unobserved heterogeneity (see Bhat and Guo, 2007; Pinjari *et al.*, 2011 for more details). These types of models are well suited for modeling cross-sectional data sources and they also overcome the limitations of the standard MNL and NL approaches (as discussed before) for modeling multi-dimensional choice processes. Similarly, Yamamoto (2009) developed trivariate binary probit model of simultaneous ownership of car, motorcycle and bicycle and Anastasopoulos *et al.* (2012) analyzed household automobile and motorcycle ownership with random parameters bivariate ordered probit model. Along similar lines, Konduri *et al.* (2011) proposed a probit-

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<sup>2</sup> To be sure, recent techniques proposed and implemented by Bhat and his colleagues (Paleti *et al.*, 2013a; Paleti *et al.*, 2013b; Paleti *et al.*, 2013c; Bhat 2011), circumvent the need to employ simulation for the computation of MNP models. However, there are still challenges associated with the deployment of these techniques for traditional transportation models.

based discrete continuous model specification for jointly modeling vehicle type choice and tour length.

### *Discrete continuous models*

In several situations, vehicle ownership decision of households may be associated with the choice of multiple alternatives simultaneously (number and types of vehicles), along with a continuous component (*e.g.* vehicle use/mileage) of choice for the chosen alternatives (Pinjari, 2011). To account for such multiple discrete-continuous choice situations, a parsimonious econometric framework termed as the multiple discrete continuous extreme value model (MDCEV) was proposed by Bhat (2005) and extended in Bhat (2008). The model has several attractive features in comparison with the conventional single discrete or discrete-continuous models. For instance, it is derived from the basic random utility theory with closed-form probability expressions and is practical even for situations with a large number of discrete consumption alternatives (Bhat and Sen, 2006; Bhat *et al.*, 2009). Since its inception, several researchers have applied the model and its variants for investigating the household vehicle holdings and use by vehicle type.

Bhat and Sen (2006) applied the mixed version of the MDCEV model that can accommodate unobserved heteroscedasticity as well as error correlations across the vehicle type utility functions. However, it does not have a closed-form probability expression, hence, requires the application of computationally intensive simulation-based estimation methods. Recently, Ahn *et al.* (2008) employed conjoint analysis and employed the MDCEV framework to understand consumer preferences for alternative fuel vehicles. In another study, Bhat *et al.* (2009) extended the MDCEV formulation to joint nested MDCEV-MNL model structure that includes a MDCEV component to analyze the choice of vehicle type/vintage and usage in the upper level and an MNL component to analyze the choice of vehicle make/model in the lower nest. Vyas *et al.* (2012) also used the same model formulation to jointly estimate the household vehicle fleet characteristics and identify the primary driver for each of the vehicles.

To be sure, the model is not without limitations. When applied to vehicle fleet composition analysis, the MDCEV model structure assumes that the process of acquiring vehicles is instantaneous, *i.e.* households choose to purchase the number of vehicles they want to own as well as the vehicle type and use decisions at a given instant. In fact, in reality, the existing household fleet ownership evolves over time with choices made in the past influencing choices in the future. Hence, it is fundamentally at odds with the more realistic process of household vehicle ownership and fails to capture the dynamics associated with vehicle transactions (Eluru *et al.*, 2010). Further, MDCEV assumes that the total utilization of vehicles (or continuous mileage component) is exogenous to the model. Similar to the MNL model, the MDCEV model also can be enhanced through nested and generalized extreme value variants to accommodate for common unobserved correlations across alternatives.

### *Copula based joint multinomial discrete-continuous model*

In recent years, the copula approach has been employed by several researchers for modeling joint distributions, such as, vehicle ownership/type and usage. One important advantage of the

approach is that the resulting model has a closed-form probability expression allowing for maximum likelihood based estimation (Bhat and Eluru, 2009). Spissu *et al.*, (2009) employed this approach to jointly analyze the type choice and utilization of the most recently purchased vehicle. The vehicle type choice component takes the familiar random utility formulation. In the modeling framework, the vehicle mileage model component would take the form of the classic log-linear regression. In this model, the copulas are used to describe the joint distribution of the error terms. The authors applied different copula functions to test the presence of different forms of dependency and found that the Frank copula model yielded the best fit.

#### *Bayesian multivariate ordered probit and tobit model (BMOPT)*

Fang (2008) developed a BMOPT model comprised of a multivariate ordered probit model with correlated covariance matrix for vehicle type choice and a multivariate Tobit model (Amemiya, 1984) for vehicle usage using data augmentation and Markov Chain Monte Carlo algorithms. The model is easy to implement and provides a simpler and more flexible framework for handling multiple-vehicle households. However, the model becomes computationally intensive with increasing vehicle categories. In another study, Brownstone and Fang (2009) extended the BMOPT model developed in Fang (2008) to treat local residential density as endogenous.

#### *Simultaneous equation system*

The model system comprises of mutually dependent discrete choice models. For instance, Chen *et al.* (2008) proposed a two-equation simultaneous equation system comprising of two endogenous variables: car ownership and the propensity to use cars. In their specification, car use for commute trips was observed but the underlying propensity to use the car was unobserved. The authors assumed that the latent propensity includes the unobserved traits/attitudes towards car use. In another study, Schimek (1996) employed this modeling technique to explore individuals' residential choices and travel decisions, with auto ownership being an intermediating variable.

Bhat and Koppelman (1993) developed an endogenous switching simultaneous equation model including husband's income, wife's income, wife's employment choice and household car ownership as endogenous variables. More specifically, car ownership choice of household was modeled as a two equation switching ordered probit model system and the wife's employment was used as the endogenous switch. The model captures the unobserved behavioural factors influencing wife's employment choice and the resulting car ownership decisions. Additionally, the model can be extended to incorporate other long term household decisions such as residential location improving the travel demand forecasting capability (Bhat and Koppelman, 1993).

#### *Structural equation model (SEM)*

In the car ownership context, structural equation models are applied to untangle the role of car ownership in mediating (car ownership can be the outcome variable in one set of relationships and at the same time, it can be a predictor of other travel behaviours) the complex relationship between the built environment and travel behaviour (see Golob *et al.*, 1996; Giuliano and Dargay, 2006; Senbil *et al.*, 2009; van Acker and Witlox, 2010; Aditjandra *et al.*, 2012). Since,

car ownership acts as an intermediate link between location decisions and travel behaviour, including it in a single equation model will result in biased results (de Abreu e Silva *et al.*, 2012).

Theoretically, SEM has two components, factor analysis/measurement model and structural equation/model (Washington *et al.*, 2011; Aditjandra *et al.*, 2012). The measurement models identify latent constructs underlying a group of manifest variables (or indicators) while the structural equations describe the directional relationship among latent and observed variables. SEM system enables us to separate out three types of effects. These are: total, direct and indirect effects of the explanatory variables. The direct effect can be interpreted as the response of the “effect” variable to the change in a “cause” variable while the indirect effect is the effect that a variable exerts on another variable through one or more endogenous variables (Gao *et al.*, 2008). The total effect is the sum of the direct and the indirect effects of a variable. For example, in the model developed by Giuliano and Dargay (2006), it is possible to measure both the direct effect of income on travel decisions and also the indirect effect, through income’s effect on car ownership, via the effect of car ownership on travel decisions.

### *Synopsis*

There is a large body of literature on joint modeling in the vehicle ownership context. These models explore the joint nature of the relationship between vehicle ownership and other decision processes (such as residential location or level of vehicle usage), thus accommodating potential endogeneity issues. The models are typically estimated using traditional cross-sectional travel survey data. To summarize, the SEM system appears to be the most popular of the joint models discussed in this section. However, the modeling method cannot adequately handle multinomial choice variables. Thus, in recent years, multidimensional choice modeling technique is gaining prominence. We found that the number of choice dimensions considered varies from 2-6 in the studies reviewed.

### Exogenous Dynamic Models

In this section we discuss the models that capture the dynamic nature of the automobile ownership decision. These models are estimated using panel data sets that possess both cross-sectional and time-series dimensions (Woldeamanuel *et al.*, 2009). Panel or longitudinal data sets are formed when sample of households are observed at multiple points in time and the observations are separated by a certain interval of time (usually one year) (Gilbert, 1992). These datasets provide analysts with multiple records for each household allowing richer model specifications incorporating intra-household and inter-household correlations. It is important to note here that due to the lack of availability of panel data several researchers have considered the use of pseudo-panel datasets – a dataset formed by stitching together multiple cross-sectional datasets is referred to as *pseudo-panel* data. The models discussed in this section include: standard discrete models, duration models and random effects models.

### *Standard discrete choice models*

Pendyala *et al.* (1995) investigated the changes in the relationship between household income and vehicle ownership using longitudinal data from the Dutch National Mobility Panel Survey.

They developed OP models for six time points to monitor the evolution of income elasticities of car ownership over time. Their analysis results indicated that elasticity of car ownership changes over time. More recently, Matas and Raymond (2008) also developed OP model using a pseudo-panel dataset.

As discussed in the exogenous static section, one important limitation of the traditional ordered model (OL or OP) is that it constrains the impact of the exogenous variables to be the monotonic for all alternatives. The recently proposed generalized ordered logit (GOL) model relaxes the monotonic effect of exogenous variables of the traditional ordered models while still recognizing the inherent ordered nature of the variable (Eluru *et al.*, 2008). Anowar *et al.* (2014b) employed the GOL framework to analyze the evolution of car ownership in Montreal, Canada. The GOL model is a flexible form of the traditional OL model that relaxes the restriction of constant threshold across population (Srinivasan, 2002, Eluru *et al.*, 2008, Eluru, 2013). The scaled GOL model is a variant of GOL that accommodates the impact of unobserved time points in the modeling approach. Specifically, a *scale parameter* is introduced in the system that scales the coefficients to reflect the changes in variance of the unobserved portion of the utility for each time point.

### *Duration models*

In the extant car ownership literature, the most common duration-model approach applied by the researchers is the hazard-based model. The model is used to investigate the automobile ownership duration as well as vehicle transaction behaviour as a function of characteristics of the car, the household and the economy (see de Jong, 1996; Yamamoto and Kitamura, 2000). The hazard function gives the probability that the ownership spell will end immediately after time  $t$ , provided that it did not end before  $t$ .

The shape of the hazard function can be chosen to be parametric, semi-parametric or non-parametric. Some examples of fully parametric functional form of hazard functions are: exponential, Weibull, log-logistic, Gompertz, log-normal, gamma, generalized gamma and generalized  $F$ . In the exponential duration model, the conditional probability of the termination of the vehicle ownership spell is the same during the entire period of ownership. Yamamoto *et al.* (1997) found that Weibull distribution provides better likelihood estimates for vehicle holding duration compared to negative exponential, Weibull, gamma, log-logistic and log-normal distributions.

According to the traditional duration analysis, the automobile ownership spell would end as a result of a single event. However, in reality, several types of events may result in the termination of the car ownership spell (*e.g.* acquire a new or used vehicle, replace with a new or used vehicle, dispose of without replacement). In such cases competing risk duration model may be estimated by defining separate hazards for each particular exit state (see Gilbert, 1992; Yamamoto *et al.*, 1999; Mohammadian and Rashidi, 2007; Yamamoto, 2008). Then the overall hazard would be the sum of all the event-specific hazards since the risks are associated with mutually exclusive events. However, Hensher and Mannering (1994) argued that such assumption of independence among risks may not be appropriate.

### *Random effects models*

Researchers have argued that inter- and/or intra-temporal correlations might exist among the observations of panel car ownership data. For example, unobserved household specific preferences (*e.g.* acquired taste for a certain lifestyle) might result in persistence in car holding decisions of households that are invariant over time which is labeled as “spurious state dependence”. On the other hand, if persistence is caused due to unobserved but time varying transaction cost (*e.g.* resistance to change in ownership levels due to search and information cost), it is termed as “true state dependence”. Both these types of state dependence have different policy implications and failure to account for these might result in biased model results (Kitamura and Bunch, 1990). Moreover, if not controlled for, it might result in overestimation of the effects of household characteristics such as income, household composition and age structure (Nolan, 2010). To account for these unobserved factors, researchers have applied random effects models which are extensions of the traditional linear regression, logit and probit models.

Nobile *et al.* (1997) proposed a random effects MNP model of household car ownership level. In their paper, the correlation is accounted for by using a general form for the error term covariance matrix. According to the authors, most of the variability in the observed choices could be attributed to between-household differences rather than within-household random disturbances.

Unlike random effects MNP model, random effects MNL model is not restricted to normal distributions and the simulation of its choice probabilities is computationally easier (Train, 2003). Moreover, with panel data, the lagged dependent variable can be added without altering the probability expression or estimation procedure. Hence, random effects logit model is considered to be more convenient than its probit counterpart for representing state dependence (see Mohammadian and Miller, 2003a; Bjorner and Leth-Petersen, 2007). The mixed logit model can be employed in two mathematically equivalent forms as random coefficients or error components (Train, 2003; Bhat *et al.*, 2008).

In another study, Anowar *et al.* (2014b) applied mixed generalized ordered logit (MGOL) model that allows the impact of observed attributes to vary across the population (in addition to accommodating impact of unobserved time points). This approach is analogous to splitting the error term into multiple error components. In this study, they used the Halton sequence (200 Halton draws) to evaluate the multidimensional integrals.

### *Synopsis*

Very few dynamic panel models can be found in the vehicle ownership literature. In terms of the model structure, researchers mostly used hazard based duration models (single and/or competing) to analyze vehicle ownership duration or vehicle transaction decision while random or mixed models were mostly employed to analyze vehicle ownership over different time periods. In our review, we found two different types of dynamic model applications: purely dynamic and pseudo-dynamic. Unfortunately, literature in the domain of dynamic analysis of vehicle ownership decision is limited, presumably due to rigorous and expensive data collection requirements. Pooling of multi-year cross-sectional data might be a potential approach for overcoming the problems associated with unavailability of panel data.

## Endogenous Dynamic Models

In this section, we focus on methods that bridge the advanced modeling techniques from endogenous static models with either panel or pseudo-panel data. In our extensive review, we found four types of endogenous dynamic modeling systems that endogenously analyzed the vehicle ownership decision. These are: copula based joint GEV based logit regression model, multinomial probit model, structural equation system and simultaneous equation system.

### *Copula based model*

Eluru *et al.* (2010a) and Paleti *et al.*, (2011) proposed a joint discrete-continuous copula based framework to investigate the simultaneity of residential location choice, vehicle count and type choice, and vehicle usage decision characteristics of households. In this framework, the decision of residential choice, and choice of no vehicle purchase or one of several vehicle types, is captured using a GEV-based logit model, while vehicle utilization (as measured by annual vehicle miles of travel or VMT) of the chosen vehicle type is modeled using a classic log-linear regression model. Moreover, the number of vehicles owned is endogenously determined as the sum of the choice occasions when the household selects a certain vehicle type. In this particular case, the number of choice occasions is linked to the number of adults in households linked with the information on the vehicle purchase sequence. The model framework can accommodate the many dimensions characterizing joint residential choice and vehicle fleet composition/usage decision system. It also has a closed-form expression for most of the copulas available in the literature and is capable of capturing the impacts of the types of vehicles already owned on the type of vehicle that might be purchased in a subsequent purchase decision.

### *Multinomial probit model (MNP)*

Paleti *et al.*, (2013b) investigated the spatial dependence effects in the fleet composition decision of households by using a MNP model. Similar to Eluru *et al.*, (2010a) and Paleti *et al.*, (2011), this model is capable of endogenously estimating the number of vehicles of each type that a household acquires by using a synthetic choice occasion approach where households are assumed to purchase vehicles over a series of choice occasions.

### *Structural Equation Model (SEM)*

Golob (1990) developed a dynamic SEM linking car ownership, travel time per week by car, travel time by public transit, and travel time by non-motorized modes. The model was developed to capture the dynamics of travel time expenditure while accounting for panel conditioning and period effects. More specifically, the model treats vehicle ownership as ordered-response probit variables and all travel times as censored (tobit) continuous variables.

### *Simultaneous equation system*

It is very likely that the previous choice or experience of owning a car may lead to a decision to acquire or dispose of a car, thereby influencing current or later levels and types of car ownership



(Hanly and Dargay, 2000; de Jong and Kitamura, 2009). To test this hypothesis, Kitamura (2009) developed a dynamic simultaneous equation system of trip generation and modal split between private car and public transit in which household car ownership level was an endogenous variable over time. In the model, each of the three elements is assumed to be dependent upon its own value at the preceding time point and this dependence is introduced by incorporating lagged dependent variables. In the equation system, the car ownership model is formulated using the ordered-response probit model, linear regression is applied to model trip generation, while the logistic response curve is used to represent modal split. Recently, Rashidi and Mohammadian (2011) proposed a dynamic hazard based system of equations for vehicle transaction, residential mobility, and employment relocation timing decisions. In their study, work location and residential relocation are included as endogenous variables.

### *Synopsis*

As is evident from above, endogenous dynamic models are still a rarity in household ownership literature. These models endeavour to capture the evolution of household's preferences over time in their vehicle purchase and/or retention decisions while considering the impact of life cycle changes and/or existing vehicle fleet information. Among the different modeling types, the joint discrete-continuous copula based framework is attractive since it can simultaneously investigate vehicle count and type choice, and vehicle usage decision characteristics of households over time.

### **3. Issues and Challenges in Vehicle Ownership Modeling**

In spite of the advances described, there are issues that pose a formidable challenge to model vehicle ownership. In this section we highlight two main emerging issues that researchers need to consider in modeling vehicle ownership: (1) data and (2) spatial correlation.

#### Data Issues

The data used to model car ownership are limited due to the amount of information available from traditional household travel surveys or other data sources. Often times, not all variables affecting the decision process is collected; either because of survey length restrictions or because "measurement" is not possible at all, resulting in omitted variable problem. For example, let us consider an omitted variable (*e.g.* environmental consciousness) which is correlated with a measured variable (*e.g.* education) and the measured variable is found to be statistically significant in the car ownership model. The observed parameter might be spurious and the factor that is actually affecting the ownership decision might be the omitted variable. Omission of such relevant variables may lead to biased and inconsistent estimates of parameters and erroneous inferences (Kitamura, 2000; Lord and Mannering, 2010). Improved methods to consider such omitted variables in a revealed preference datasets need to be developed (see an example of such methods in the context of stated preference data for vehicle ownership in Daziano and Bolduc, 2013).

Another challenge with the data is the failure to recognize that travel behavior and urban form are evolving in continuous time. Rather than studying vehicle ownership as a snapshot using

cross-sectional data, it is useful to consider the changes happening across time. Unfortunately, collection of panel data is prohibitively expensive, time consuming and has very low response retention rates. As an alternative, in recent times, a pseudo-panel approach that stitches together a series of cross-sectional datasets is used by the researchers to estimate dynamic car ownership models. These studies employ exogenous variable cohort averages in the analysis (Dargay and Vythoulkas, 1999; Dargay, 2002), thus resulting in a loss of data resolution. A more recent research effort that considers exogenous variables at a disaggregate level while explicitly accounting for unobserved correlation across each cross-section offers promise (Anowar *et al.*, 2014a).

### Spatial Correlation

The decision of vehicle fleet size and type might be heavily influenced by the choices made by neighbouring households (Adjemian *et al.*, 2010). If the neighbours own and drive hybrid electric vehicles, that household might become more environmentally conscious and purchase a hybrid electric vehicle (Chan *et al.*, 2011; Paleti *et al.*, 2013b). Spatial interdependence might also arise from unobserved attitudinal preferences such as peer pressure from social networks (Axsen and Kurani, 2012). That is, households who have a proclivity towards similar lifestyles might “cluster together” in neighbourhoods that support their lifestyle preferences (Eluru *et al.*, 2010a). Failure to account for such potential interdependence might result in biased parameter estimates. However, estimation of the discrete choice models accommodating spatial dependence effect requires evaluation of multidimensional integrals making the process intractable. A more recent effort proposed by Paleti *et al.*, (2013b) is tractable and avoids simulation offering promise to incorporate spatial correlation in vehicle ownership studies.

## 4. Summary and Conclusions

This paper reviewed the disaggregate models examining household vehicle ownership that are developed over the last two decades (since 1990) using a four-way classification of the modeling frameworks. Specifically, the four model types discussed in detail are: exogenous static, endogenous static, exogenous dynamic and endogenous dynamic. In each category, we begin by discussing the rudimentary models and then proceed on explaining the more complex models. Included in the discussion are the mathematical concepts behind the model development as well as the underlying behavioural reasoning, in the vehicle ownership context.

The research efforts using standard models in the exogenous static group offer useful insights on the role of exogenous variables (e.g. household socio-demographics, land use and urban form attributes, transit and infrastructure characteristics) on vehicle ownership decision processes. On the other hand, the endogenous models are motivated from the need to accurately analyze the interdependencies between different influential elements associated with vehicle ownership. Two major modeling streams can be found in the literature in this regard: joint discrete choice models involving nominal and/or ordinal endogenous variables, and structural equation models (SEM) involving continuous endogenous variables. The joint discrete choice models do not allow direct causality between their endogenous variables. Contrastingly, SEMs assumes direct mutual causality among endogenous variables. Simultaneous equation systems conceptually blend both these approaches, jointly modeling discrete endogenous variables as mutually dependent. More

recent research on vehicle ownership has adopted dynamic models (exogenous and endogenous) that analyze vehicle ownership as a behavioural process that evolves over time. The common techniques employed in this domain include hazard based duration models, mixed effects model and structural equation models.

In summary, the choice of model/s is guided by the objectives to be accomplished or issues to be addressed, data availability and most importantly, the nature of the dependent variable/s. In an attempt to aid researchers and practitioners, based on our extensive review and judgement, we provide a useful decision matrix table (see Table 2) for determining the appropriate model for various vehicle ownership contexts. We close with a cautionary advice that it is important to recognize that advanced models are not a substitute for accommodating observed heterogeneity in traditional models.

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**Table 1:** Summary of previous researches on automobile ownership

Studies	Data Source & Type	Modeling Approach	Vehicle Demand Form	Variables Considered							Unobserved Effects
				Household Demographic	Individual Attributes	Employment Attributes	Life Cycle Attributes	Built Environment	Transit Attributes	Policy	
Exogenous Static (32)											
Karlaftis and Golias (2002)	Greece <i>Roadside Interviews</i>	Binary logit	VO	√	-	-	√	√	√	√	-
Li <i>et al.</i> (2010)	China <i>Household Survey</i>	Binary logit	VO	√	√	√	√	√	√	-	-
Ma and Srinivasan (2010)	USA <i>Census micro-data</i>	Binary probit	VO	√	√	-	√	√	-	-	-
Whelan (2007)	Great Britain <i>Travel Survey</i>	Binary dogit	VO	√	-	-	-	√	-	√	-
Bhat and Pulugurta (1998)	USA <i>Activity Survey</i> Netherlands <i>Travel Survey</i>	Ordered logit	VO	√	-	-	-	√	-	-	-
Hess and Ong (2002)	USA <i>Activity and Travel Survey</i>	Ordered logit	VO	√	√	-	-	√	√	-	-
Kim and Kim (2004)	USA <i>Travel Survey</i>	Ordered logit	VO	√	-	-	√	√	√	-	-
Potoglou and Susilo (2008)	USA Netherlands Japan <i>Travel Survey</i>	Ordered logit	VO	√	√	-	√	√	-	-	-
Potoglou and Kanaroglou (2008b)	Canada <i>Internet Survey</i>	Ordered logit	VO	√	-	√	√	√	√	-	-
Chu (2002)	USA <i>Travel Survey</i>	Ordered probit	VO	√	-	√	√	√	-	-	-
Cao <i>et al.</i> (2007a)	USA <i>Attitudinal Survey</i>	Ordered probit	VO	√	√	-	-	√	-	-	√
Potoglou and Susilo (2008)	USA Netherlands Japan <i>Travel Survey</i>	Ordered probit	VO	√	√	-	√	√	-	-	-

Ma and Srinivasan (2010)	USA <i>Census micro-data</i>	Ordered probit	VO	√	√	-	√	√	-	-	-
Bhat and Pulugurta (1998)	USA <i>Activity Survey</i> Netherlands <i>Travel Survey</i>	Multinomial logit	VO	√	-	-	-	√	-	-	-
Wu <i>et al.</i> (1999)	China <i>Stated Preference Survey</i>	Multinomial logit	VT	√	√	√	√	√	√	√	-
Ryan and Han (1999)	USA <i>Census micro-data</i>	Multinomial logit	VO	√	-	-	-	√	-	-	-
Choo and Mokhtarian (2004)	USA <i>Attitudinal Survey</i>	Multinomial logit	VT	√	√	√	√	√	-	-	-
Bento <i>et al.</i> (2005)	USA <i>Travel Survey</i>	Multinomial logit	VO	√	√	-	√	√	√	√	-
Soltani (2005)	Australia <i>Travel Survey</i>	Multinomial logit	VO	√	-	-	√	√	√	-	-
Potoglou and Kanaroglou (2008b)	Canada <i>Internet Survey</i>	Multinomial logit	VO	√	-	√	√	√	√	-	-
Potoglou and Susilo (2008)	USA Netherlands Japan <i>Travel Survey</i>	Multinomial logit	VO	√	√	-	√	√	-	-	-
Potoglou (2008)	Canada <i>Internet Survey</i>	Multinomial logit	VT	√	√	-	√	√	-	-	-
Zegras (2010)	Chile <i>OD Survey</i>	Multinomial logit	VO	√	-	-	-	√	√	-	-
Caulfield (2012)	Ireland <i>Census Data</i>	Multinomial logit	VO	√	√	-	√	√	√	-	-
Wong (2013)	Macao <i>Travel Survey</i>	Multinomial logit	VO	√	-	-	√	√	-	-	-
McCarthy and Tay (1998)	USA <i>Consumer Survey</i>	Nested logit	VT	√	-	-	√	√	-	√	-
Kermanshah and Ghazi (2001)	Iran <i>Travel Survey</i>	Nested logit	VO	√	-	√	√	√	-	-	-
Mohammadian and Miller (2002)	Canada <i>Retrospective Survey</i>	Nested logit	VT	√	√	√	-	-	-	√	-

Mohammadian and Miller (2003b)	Canada <i>Retrospective Survey</i>	Nested logit	VT	√	√	√	-	-	-	√	-
Cao <i>et al.</i> (2006)	USA <i>Attitudinal Survey</i>	Nested logit	VT	√	√	-	√	√	-	-	-
Guo (2013)	USA <i>Travel Survey</i>	Nested logit	VO	√	-	√	-	√	√	-	-
Potoglou (2008)	Canada <i>Internet Survey</i>	Random parameters logit	VT	√	√	-	√	√	-	-	-
Shay and Khattak (2011)	USA <i>Travel Survey</i>	Poisson regression	VO	√	-	-	-	√	-	-	-
Shay and Khattak (2005)	USA <i>Travel Survey</i>	Negative binomial regression	VO	√	-	-	-	√	-	-	-
Shay and Khattak (2007)	USA <i>Travel Survey</i>	Negative binomial regression	VO	√	-	-	-	√	√	-	-
Karlaftis and Golias (2002)	Greece <i>Roadside Interviews</i>	Poisson-lognormal model	VO	√	-	-	√	√	√	√	-
Anowar <i>et al.</i> (2014a)	Canada <i>OD Survey</i>	Latent class multinomial logit	VO	√	-	√	-	√	√	-	-
Anowar <i>et al.</i> (2014a)	Canada <i>OD Survey</i>	Latent class ordered logit	VO	√	-	√	-	√	√	-	-
Beck <i>et al.</i> (2013)	Australia <i>Interviewer Assisted Online Survey</i>	Latent class multinomial logit	VT	-	-	-	-	-	-	√	-
Mohammadian and Miller (2002)	Canada <i>Retrospective Survey</i>	Artificial Neural Network	VT	√	√	√	-	-	-	√	-
<b>Endogenous Static (29)</b>											
Dissanayake and Morikawa (2002)	Thailand <i>Travel Survey</i>	Nested logit	VO	√	√	√	√	-	-	-	√
Salon (2009)	USA <i>Travel Survey</i>	Multinomial logit	VO	√	-	-	√	√	√	√	√
Weinberger and Goetzke (2010)	USA <i>Census Micro-Data</i>	Multinomial probit	VO	√	√	-	√	√	-	-	√
Bhat and Guo (2007)	USA <i>Travel Survey</i>	Mixed multidimensional choice modeling	VO	√	-	-	-	√	√	-	√
Yamamoto (2009)	Japan Malaysia <i>Trip Survey</i>	Trivariate binary probit	VO	√	-	-	-	√	√	-	√

Pinjari <i>et al.</i> (2011)	USA <i>Travel Survey</i>	Mixed multidimensional choice modeling	VO	√	√	-	√	√	√	√	√
Konduri <i>et al.</i> (2011)	USA <i>Travel Survey</i>	Probit-based joint discrete continuous model	VT	√	√	-	√	√	-	-	√
Anastasopoulos <i>et al.</i> (2012)	Greece <i>Travel Survey</i>	Random parameters bivariate ordered probit	VO	√	√	√	-	√	√	-	√
Paleti <i>et al.</i> (2013a)	USA <i>Travel Survey</i>	Mixed multidimensional choice modeling	VO	√	-	-	√	√	-	-	√
Paleti <i>et al.</i> (2013c)	USA <i>Travel Survey</i>	Bivariate multinomial probit	VO	√	-	√	√	√	-	-	√
Bhat and Sen (2006)	USA <i>Travel Survey</i>	Mixed multiple discrete continuous extreme value model	VT & VU	√	-	-	√	√	-	√	√
Ahn <i>et al.</i> (2008)	South Korea <i>Face-to-face Interview</i>	Mixed multiple discrete continuous extreme value model	VO & VU	-	-	-	-	-	-	√	√
Bhat <i>et al.</i> (2009)	USA <i>Travel Survey</i>	Joint nested multiple discrete continuous extreme value model	VT & VU	√	√	-	√	√	√	√	√
Vyas <i>et al.</i> (2012)	USA <i>Vehicle Survey</i>	Joint nested multiple discrete continuous extreme value model	VT & VU	√	√	-	√	√	-	-	√
Spissu <i>et al.</i> (2009)	USA <i>Travel Survey</i>	Copula based joint multinomial discrete-continuous model	VT & VU	√	√	-	√	√	√	-	√
Fang (2008)	USA <i>Travel Survey</i>	Bayesian multivariate ordered probit and tobit model	VO & VU	√	√	-	√	√	-	-	√

Brownstone and Fang (2009)	USA <i>Travel Survey</i>	Bayesian multivariate ordered probit and tobit	VO & VU	√	√	-	√	√	√	-	√
Schimek (1996)	USA <i>Travel Survey</i>	Two-equation system simultaneous equation model	VO & VU	√	√	-	√	√	√	-	√
Chen <i>et al.</i> (2008)	USA <i>Travel Survey</i>	Two-equation system simultaneous equation model	VO & VU	√	√	-	√	√	√	√	√
Bhat and Koppelman (1993)	Netherlands <i>Travel Survey</i>	Endogenous switching simultaneous equation model	VO	√	√	-	-	√	-	-	√
Golob <i>et al.</i> (1996)	USA <i>Telephone Survey &amp; SP Survey</i>	Cross-sectional structural equation model	VT & VU	√	√	√	√	-	-	√	√
Golob <i>et al.</i> (1997)	USA <i>Telephone Survey &amp; SP Survey</i>	Cross-sectional structural equation model	VT & VU	√	√	√	√	-	-	√	√
Giuliano and Dargay (2006)	USA Great Britain <i>Travel Survey</i>	Cross-sectional structural equation model	VO & VU	√	√	√	√	√	√	-	√
Cao <i>et al.</i> (2007b)	USA <i>Attitudinal Survey</i>	Structural equation model	VO	√	√	-	√	-	-	-	√
Gao <i>et al.</i> (2008)	USA Census Tract Data	Cross-sectional structural equation model	VO	√	√	√	-	-	-	-	√
Senbil <i>et al.</i> (2009)	Japan Malaysia <i>Travel Survey</i>	Cross-sectional structural equation model	VO	√	√	-	-	√	√	√	√
van Acker and Witlox (2010)	Belgium <i>Travel Behaviour Survey</i>	Cross-sectional structural equation model	VO & VU	√	√	√	-	√	-	-	√
de Abreu e Silva <i>et al.</i> (2012)	Canada <i>OD Survey</i>	Cross-sectional structural equation model	VO & VU	√	√	√	√	√	-	-	√



Aditjandra <i>et al.</i> (2012)	Great Britain <i>Quasi-longitudinal Data</i>	Quasi-longitudinal structural equation model	VO	√	√	-	-	√	-	-	√
<b>Exogenous Dynamic (16)</b>											
Prillwitz <i>et al.</i> (2006)	Germany <i>Panel Waves</i>	Binary probit	VO	√	√	√	√	√	-	-	-
Yamamoto (2008)	Japan <i>Panel Survey</i>	Multinomial logit	VTR	√	-	-	√	√	√	-	-
Pendyala <i>et al.</i> (1995)	Netherlands <i>Mobility Panel Survey</i>	Ordered probit	VO	√	-	-	-	√	√	-	-
Matas and Raymond (2008)	Spain <i>Pseudo-Panel</i>	Ordered probit	VO	√	√	-	√	√	√	-	-
Anowar <i>et al.</i> (2014b)	Canada <i>Pseudo-Panel</i>	Scaled generalized ordered logit	VO	√	-	-	√	√	√	-	√
de Jong (1996)	Netherlands <i>Vehicle Panel Survey</i>	Single hazard duration model	VOD	√	√	-	-	-	-	√	√
Yamamoto and Kitamura (2000)	USA <i>Panel Survey</i>	Single hazard duration model	VOD	√	√	√	-	-	-	-	√
Gilbert (1992)	USA <i>Panel Survey</i>	Competing hazards duration model	VTR	√	√	√	√	-	-	-	-
Yamamoto <i>et al.</i> (1999)	USA <i>Panel Survey</i>	Competing hazards duration model	VTR	√	-	√	√	-	-	-	-
Mohammadian and Rashidi (2007)	Canada <i>Retrospective Survey</i>	Competing hazards duration model	VTR	√	√	√	√	√	-	√	√
Yamamoto (2008)	France <i>Panel Survey</i>	Competing hazards duration model	VTR	√	-	-	√	√	√	-	-
Kitamura and Bunch (1990)	Netherlands <i>Mobility Panel Survey</i>	Random effects ordered probit	VO	√	√	-	√	-	√	-	√
Nobile <i>et al.</i> (1997)	Netherlands <i>Mobility Panel Survey</i>	Random effects multinomial probit model	VO	√	-	-	√	√	-	-	√
Mohammadian and Miller (2003a)	Canada <i>Retrospective Survey</i>	Mixed parameter logit	VTR & VT	√	-	-	-	-	-	√	√

Bjorner and Leth-Petersen (2007)	Denmark <i>Panel Survey</i>	Random effects multinomial logit model	VO	√	√	√	-	√	-	√	√
Woldeamanuel <i>et al.</i> (2009)	Germany <i>Panel Survey</i>	Random effects regression	VO	√	-	-	-	√	√	√	√
Nolan (2010)	Ireland <i>Panel Survey</i>	Random effects binary probit	VO	√	√	-	√	√	-	-	√
Anowar <i>et al.</i> (2014b)	Canada <i>Pseudo-Panel</i>	Mixed generalized ordered logit	VO	√	-	-	√	√	√	-	√
<b>Endogenous Dynamic (6)</b>											
Eluru <i>et al.</i> (2010a)	USA <i>Travel Survey</i>	Copula based joint GEV-based logit-regression model	VT & VU	√	-	-	√	√	√	-	√
Paleti <i>et al.</i> (2011)	USA <i>Vehicle Survey</i>	Copula based joint GEV-based logit-regression model	VT & VU	√	√	-	√	√	-	√	√
Paleti <i>et al.</i> (2013b)	USA <i>Travel Survey</i>	Multinomial probit model	VT	√	√	√	√	√	-	-	√
Golob (1990)	Netherlands <i>Mobility Panel Survey</i>	Longitudinal structural equation model	VO	√	-	-	√	√	-	-	√
Kitamura (2009)	Netherlands <i>Mobility Panel Survey</i>	Three equation simultaneous equation model	VO	√	√	-	√	√	√	-	√
Rashidi and Mohammadian (2011)	USA <i>Travel Panel Survey</i>	Hazard based Simultaneous equation model	VTR	√	√	-	-	√	√	-	√
<i>Note: VO = vehicle ownership; VT = vehicle type; VU = vehicle use; VOD = vehicle ownership duration; VTR = vehicle transaction; OD = origin-destination</i>											

**Table 2: Decision matrix for Vehicle Ownership Model Selection**

Vehicle Demand	Suggested Model			
	Exogenous Static	Endogenous Static	Exogenous Dynamic	Endogenous Dynamic
Vehicle count				
<i>No heterogeneity</i>	Generalized ordered logit	Multidimensional choice modeling	-	Simultaneous equation model
<i>Heterogeneity</i>	Latent class multinomial logit	Mixed multidimensional choice modeling	Mixed generalized ordered logit	-
Vehicle count and use	-	Multiple discrete continuous extreme value model	-	-
Vehicle type				
<i>No heterogeneity</i>	Multinomial logit	-	-	Multinomial probit
<i>Heterogeneity</i>	Mixed multinomial logit	-	-	-
Vehicle type and use	-	Copula based joint multinomial discrete continuous model	-	Copula based joint GEV-based logit-regression model
Vehicle ownership duration	-	-	Duration model (single hazard)	-
Vehicle transaction	-	-	Duration model (competing hazards)	Hazard based Simultaneous equation model
Vehicle transaction and type	-	-	Mixed parameter logit	-