

Modeling Household Vehicle Holdings and Composition: A Multi-Dimensional Analysis of Vehicle Body-Type and Fuel-Type Choices

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ABSTRACT

Household vehicle ownership and fleet composition are being reshaped by electric vehicle diffusion, rising SUV preferences, and gasoline price volatility. Yet existing models rarely ensure consistency between overall household vehicle fleet size and preferences for specific vehicle types. This study aims to develop a model of household vehicle holdings that jointly estimates vehicle counts by body-type and fuel-type, addressing the need for more accurate behavioral models to inform travel forecasts and planning policy. A multivariate ordered probit model jointly estimates total household vehicle ownership alongside vehicle counts across 12 body-type/fuel-type combinations. The model uses data from Wave 1 of the Transportation Heartbeat of America Survey, a national U.S. survey of more than 8,000 residents conducted October 2024 through January 2025. Three stochastic latent constructs (green lifestyle propensity, safety consciousness, and vehicle status perception) are estimated jointly with the main outcomes using a two-stage generalized heterogeneous data modeling approach. Average treatment effects are computed to quantify the influence of variables on choice outcomes. Green lifestyle propensity, safety consciousness, and vehicle status perception each significantly shape fleet composition. Electric vehicles, across nearly every body-type, are significantly more common among households with three or more vehicles. Income continues to be very significant determinant of vehicle ownership and EV adoption. The joint model significantly outperforms an independent model estimated separately for each outcome across all fit measures. This study is among the first to jointly estimate total household vehicle counts and detailed body-type/fuel-type counts within a single ordered-response framework, directly capturing how fleet size, together with attitudinal and demographic variables, shapes vehicle-type preferences. Findings suggest electric vehicle incentives may achieve greater near-term impact when targeted toward multi-vehicle households, and the joint framework supports more realistic fleet forecasts for infrastructure, charging, and multimodal planning.

Keywords: Household vehicle holdings, vehicle fleet composition, electric vehicles, multivariate ordered probit, lifestyle preferences, behavioral modeling, vehicle preferences, travel attitudes

1. INTRODUCTION

Passenger transportation in the United States remains heavily reliant on private motorized vehicles. This reliance stems from a combination of factors, including the widespread availability of public roads and parking relative to the comparatively limited reach of public transit, the mobility control and reliability that private vehicle travel affords compared to alternative modes, and the social expectations and status that vehicle ownership continues to confer (Moody and Zhao, 2020; Soza-Parra and Cats, 2024). At the same time, this pervasive reliance on private vehicles carries substantial societal costs, contributing to elevated levels of traffic congestion, adverse environmental impacts, and diminished health outcomes (Boogaard et al., 2022; Fan and Harper, 2022; Miner et al., 2024). Vehicle ownership also directly shapes household transportation expenditures, imposing a significant economic burden on many households and contributing to transportation insecurity among those without access to a vehicle (Morris et al., 2020; Moody et al., 2021).

Beyond the overall reliance on private vehicles, the specific types of vehicles that households own — in terms of both body-type and fuel-type — determine the nature and magnitude of these impacts at both the household and societal level. Vehicles of different body-types offer distinct advantages depending on household needs, including the suitability of larger vehicles for accommodating household or non-household passengers, differences in ride comfort, and variation in available safety features (Khan and Habib, 2021). Vehicle type also interacts with road environment and trip purpose in determining suitability (Potoglou, 2008), and different vehicle types carry markedly different implications for congestion, emissions, and roadway safety (Anderson and Auffhammer, 2014; Winston and Yan, 2021).

While patterns of household vehicle ownership have been studied extensively, several recent trends motivate a fresh look at household vehicle holdings and composition. First, there is evidence that households became more reliant on private vehicles during the pandemic (Basu and Ferreira, 2021; Iogansen et al., 2025), shifting away from public transit and other shared modes with little indication of returning to pre-pandemic travel patterns (Smith et al., 2025). Second, the growing availability of electric vehicles requires renewed attention to how households weigh fuel-type considerations alongside other vehicle attributes; much of the existing literature has focused on electric vehicle adoption in isolation, yet the emissions benefits of electrification depend critically on how electric vehicles are used and which vehicles they replace, or fail to replace, within the household fleet (Xing et al., 2021). Third, continued price volatility in the gasoline market and the accelerating adoption of larger sport utility vehicle body-types further complicate household vehicle type preferences, underscoring the need for models capable of capturing this rapidly evolving vehicle ownership landscape.

Existing studies examining household vehicle holdings are also limited in two important respects. First, many rely on the multiple discrete-continuous extreme value (MDCEV) framework, which has been widely applied to model vehicle holdings and utilization by identifying which vehicle type alternatives a household selects and how intensively each is used (Bhat and Sen, 2005; Bhat et al., 2009; Augustin et al., 2015; Chakraborty et al., 2023). However, this formulation identifies only whether at least one vehicle of a given type is held, rather than the exact count of vehicles held within each category. Second, existing studies generally do not allow the total size of the household vehicle fleet to directly influence preferences for specific vehicle types. Yet households may value certain vehicle types quite differently depending on whether that vehicle would serve as a primary or a secondary vehicle in the household fleet. In the context of electric vehicles, for example, a multi-vehicle household may be more willing to adopt an electric

vehicle precisely because any perceived range or reliability risk is mitigated by the flexibility of a gasoline vehicle already in the fleet. In contrast, a household considering an electric vehicle as its sole vehicle may be considerably more circumspect, a pattern born out later in the model results presented in this paper.

This study addresses these gaps by presenting a model of household vehicle holdings and composition based on a multivariate ordered probit formulation that directly estimates the number of vehicles a household owns across each of 12 vehicle body-type/fuel-type combinations. The model is designed to examine the effects of household demographics and latent lifestyle perceptions on vehicle holdings, while also determining how the overall size of a household's vehicle fleet shapes preferences for specific vehicle types. Critically, the multivariate ordered probit structure allows for direct estimation of the total number of vehicles alongside the number of vehicles held in each body-type/fuel-type category, while maintaining internal consistency across these dimensions. The formulation further accommodates unobserved correlations across the 13 count outcomes (one for the number of vehicles, plus 12 additional for each body-type/fuel-type combination), recognizing that some households may possess a generic underlying propensity toward higher levels of vehicle ownership while simultaneously exhibiting distinct preferences for specific vehicle types.

Beyond advancing understanding of household vehicle preferences, this research effort is intended to help advance and inform transportation planning and public policy. Household decisions regarding both fleet size and vehicle composition directly shape future travel demand, transportation energy consumption, emissions, roadway infrastructure needs, parking demand, and charging infrastructure requirements. As governments continue to promote transportation electrification through incentives and infrastructure investment, there is a growing need for behavioral models capable of jointly evaluating how household characteristics and preferences shape both the number of vehicles owned and the composition of the household vehicle fleet.

To accomplish this objective, the study draws on data collected in Wave 1 of the Transportation Heartbeat of America (THA) Survey, a national survey conducted between October 2024 and January 2025. The survey gathered detailed information on household vehicle holdings by body-type and fuel-type, along with socio-economic, demographic, and attitudinal characteristics of respondents, offering a timely and nationally representative lens through which to examine evolving vehicle ownership patterns.

The remainder of this paper is organized as follows. The next section describes the survey and data used in this study. This is followed by a discussion of the model formulation, presentation and discussion of model estimation results, and concluding thoughts on the planning and policy implications of the study findings.

2. DATA DESCRIPTION

This section summarizes the data set used in this study. The survey and sample characteristics are described first, followed by a more detailed description of the outcomes and latent constructs considered in the current analysis.

2.1. Survey Overview and Sample Characteristics

The data used in this study were collected in Wave 1 of the Transportation Heartbeat of America (THA) Survey, administered from October 2024 through January 2025. Recruitment was conducted through a Qualtrics opinion panel using a quota-based sampling approach designed to ensure a reasonable sample size across multiple demographic subgroups, including race, ethnicity,

age, gender, education, and household income, as well as across geographically defined residence areas encompassing urban and rural residence and each of the nine U.S. census divisions. Eligible participants included all individuals residing in the United States aged 18 years or older, and multiple attention checks and quality control measures were incorporated to ensure response quality. A complete description of the survey and sample characteristics is available in Robbennolt et al. (2025a).

The survey covers a broad range of topics, including general transportation-related attitudes, values and preferences regarding economic investment in transportation infrastructure, intentions regarding emerging and future transportation technologies, preferences for online activity participation, and current transportation behaviors, including household vehicle holdings. In particular, respondents were asked to provide detailed information on the number of vehicles owned by household members, along with each vehicle's vintage, body-type, and fuel-type.

Additional built environment measures were appended to each survey record from the EPA Smart Location Database (Chapman et al., 2021) based on the respondent's zip code of residence. These include the population density, used to categorize each household as urban or rural; a land use diversity index reflecting the balance of trip productions and attractions¹; car network density, defined as the number of auto-oriented link-miles per square mile; a national walkability index²; and a transit accessibility measure based on the proportion of employment opportunities located within a half-mile of a fixed-guideway transit stop.

We should note that the THA survey was collected at an individual level (with one respondent per household) rather than at the level of the entire household. Vehicle ownership choices, admittedly, reflect household-level decision processes that reflect the characteristics, needs, and attitudes of all household members. Therefore, where possible, exogenous variables were constructed to reflect household-level characteristics rather than those of the individual. For example, rather than using the age of the respondent, the age of the oldest household member was used to represent the household's life-cycle stage. However, a few variables (including race and education) remain at the individual level, and the attitudinal latent constructs (see Section 2.3) reflect the attitudes only of the respondent. Still, there is good reason to believe that even these individual-level characteristics and attitudes serve as reasonable proxies for household-level characteristics given evidence from the demography literature of strong individual-household correspondence for characteristics such as race and educational attainment (see Bratter et al., 2022; Hofmeister et al., 2025) as well as evidence from the sociology and psychology literature that attitudes and lifestyle preferences tend to be strongly correlated across family members, particularly among those in joint decision making roles (see Zablocki and Kanter, 1976; Chambers and Gracia, 2021; Nguyen et al., 2024). For consistency, for the remainder of the paper, we refer to the household as the decision-making unit rather than the individual or respondent.

The full THA Wave 1 dataset includes 8,212 complete responses; after data cleaning, 7,864 observations are retained for the final analysis conducted in this study. The demographic

¹The land-used diversity index takes values between zero and one. It was calculated first at the census block group level, based on the number of trip productions and attractions in each census block group, and then aggregated to the zip code level along with the other built-environment measures. Production and attraction calculations were performed based on average Institute of Transportation Engineers trip generation rates. A value of one indicates balanced trip making with equal levels of trip production and attraction, which values close to zero indicate a high degree of imbalance.

²This is the Smart Location Database National Walkability Index, which takes values between one and twenty based on ranked scores for (1) employment and household entropy, (2) static eight tier employment entropy, (3) pedestrian-oriented street intersection density, and (4) distance to the nearest transit stop.

characteristics of the analysis sample are presented in the upper section of Table 1. The age distribution skews somewhat older, with 29.8 percent of households having an oldest member aged 65 years or older, compared to only 4.9 percent where the oldest member is aged 18 to 24 years. The remaining age categories for the oldest members are fairly evenly distributed, with 17.2 percent aged 35 to 44 years and 20.0 percent aged 55 to 64 years. Household size is skewed toward larger households, with 47.4 percent comprising three or more members, 32.9 percent comprising two members, and 19.7 percent comprising a single member. In terms of employment, 39.3 percent of households have two or more employed adults, 32.8 percent have one employed adult, and 27.9 percent have no employed adults.

Stand-alone homes make up the majority of the housing stock represented in the sample (66.9 percent), with 26.8 percent of respondents residing in attached homes or apartments. Homeownership is similarly prevalent, with 59.8 percent of households owning their residence and 35.5 percent renting. The sample reflects considerable racial and ethnic diversity, with 63.1 percent identifying as White, 14.8 percent as Black, 7.6 percent as Asian or Pacific Islander, and 14.5 percent as another race. Nearly 20 percent of respondents identify as Hispanic. Educational attainment is spread broadly across categories, with 32.6 percent having a high school education or less, 29.5 percent having some college or technical school training, 22.9 percent holding a bachelor's degree, and 15.0 percent holding a graduate degree.

TABLE 1: Sample Demographic Characteristics and Vehicle Holdings (N=7,864)

Demographics							
Variable		%	Variable		%		
Age of eldest household member			Annual household income				
18 to 24 years		4.9	Less than \$25,000		16.7		
25 to 34 years		10.7	\$25,000 to \$49,999		21.8		
35 to 44 years		17.2	\$50,000 to \$99,999		30.7		
45 to 54 years		17.4	\$100,000 to \$149,999		19.5		
55 to 64 years		20.0	\$150,000 to \$199,999		7.3		
65 years or older		29.8	\$200,000 or more		4.0		
Household size			Number of employed adults				
One		19.7	Zero		27.9		
Two		32.9	One		32.8		
Three or more		47.4	Two or more		39.3		
Housing unit type			Homeownership status				
Stand-alone home		66.9	Own		59.8		
Attached home/apartment		26.8	Rent		35.5		
Other		6.3	Other		4.7		
Race			Educational attainment				
Asian or Pacific Islander		7.6	High school or less		32.6		
Black		14.8	Some college or technical school		29.5		
White		63.1	Bachelor’s degree(s)		22.9		
Other		14.5	Graduate degree(s)		15.0		
Ethnicity			Location				
Hispanic		19.8	Urban		84.6		
Non-Hispanic		80.2	Rural		15.4		
Main Outcome Variables							
Vehicle ownership							
Zero					8.9		
One					40.8		
Two					34.7		
Three					10.6		
Four					3.8		
Five or more					1.2		
Vehicle holdings			0	1	2	3	4
Gasoline SUV			54.2	37.3	7.5	0.8	0.2
Electric SUV			96.5	3.3	0.2	--	--
Gasoline sedan			61.7	31.8	5.7	0.7	0.1
Electric sedan			97.6	2.3	0.1	--	--
Gasoline pickup			79.7	18.4	1.8	0.1	--
Electric pickup			99.6	0.4	--	--	--
Gasoline compact			87.8	11.2	0.9	0.1	--
Electric compact			98.9	1.0	0.1	--	--
Gasoline minivan			94.2	5.5	0.3	--	--
Electric minivan			99.8	0.2	--	--	--
Gasoline sports car			93.7	5.6	0.5	0.2	--
Electric sports car			99.2	0.8	--	--	--

Household income is concentrated in the middle range, with 30.7 percent of households earning between \$50,000 and \$99,999 annually and 21.8 percent earning between \$25,000 and \$49,999; households at the extremes are comparatively less common, with 16.7 percent earning less than \$25,000 and only 4.0 percent earning \$200,000 or more. Finally, the sample is predominantly urban, with 84.6 percent of respondents residing in urban areas and 15.4 percent in rural areas, consistent with the overall urban concentration of the U.S. population. Overall, the sample reflects considerable variation in socio-economic and demographic attributes, rendering it well-suited for the multivariate modeling exercise undertaken in this research study.

As noted above, the survey was designed with sampling quotas ensuring a reasonable level of representation with the overall United States population in terms of key demographics. This also ensured that the sample is sizeable, encompasses the entire nation, and has substantial variation in each of the exogenous characteristics considered. Therefore, even if some discrepancies remain between the survey exogenous characteristics and the overall United States population, there is no reason to believe that the relationships estimated in the household-level model would not apply to the population at large. Further, an unweighted approach is preferred to a weighted estimation approach because the sample was collected exogenously (there was no targeting based on households with specific vehicles or fleet compositions), implying that an unweighted estimator is more efficient (see Robbennolt, et al., 2026).

2.2. Endogenous Outcomes

The main outcomes examined in this study consist of a set of 13 ordered-response variables: the total count of vehicles owned by the household, and the number of vehicles owned in each of 12 body-type/fuel-type combinations. The 12 combinations are constructed from six vehicle body-types — SUV, pickup truck, sedan, compact, minivan, and sports car — crossed with two fuel-types, internal combustion engine (including non-plug-in hybrid vehicles) and electric (including plug-in hybrid and fully electric vehicles). A total of 144 respondents who indicated "Other" in response to the vehicle type question were removed from the analysis sample, as their vehicles could not be classified into one of the six body-types considered. Reported vehicle counts were capped at five, with respondents owning more than five vehicles asked to report only the five vehicles used most often; the largest number of vehicles of a single body-type/fuel-type combination reported by any respondent was four.

Descriptive statistics for household vehicle ownership are presented at the bottom of Table 1. Overall vehicle ownership levels are substantial, with 40.8 percent of households owning one vehicle and 34.7 percent owning two vehicles; smaller shares of households own three vehicles (10.6 percent), four vehicles (3.8 percent), or five or more vehicles (1.2 percent), while 8.9 percent of households report owning no vehicle at all.

Examining ownership patterns across the 12 body-type/fuel-type combinations reveals a clear and consistent picture: electric vehicles remain relatively uncommon across all body-types, underscoring the still-limited penetration of electric vehicles nationally. For every body-type considered, the share of households owning zero electric vehicles exceeds 96 percent, with electric pickups, minivans, and sports cars in particular owned by less than one percent of households at even a single-vehicle level. Gasoline vehicles, in contrast, are far more prevalent. SUVs and sedans emerge as the dominant body-types in the household fleet, with 45.8 percent of households owning at least one gasoline SUV and 38.3 percent owning at least one gasoline sedan; a nontrivial share of households own two or more of each (8.5 percent for gasoline SUVs and 6.5 percent for gasoline sedans). Gasoline pickups and compacts are moderately common, owned by 20.3 percent and 12.2

percent of households, respectively, though multi-vehicle ownership within these categories is comparatively rare. Minivans and sports cars are the least common body-types across both fuel-types, with gasoline minivans and gasoline sports cars owned by only 5.8 percent and 6.3 percent of households, respectively, and their electric counterparts owned by less than one percent. Taken together, these patterns reflect a household vehicle fleet that remains overwhelmingly gasoline-powered and concentrated in SUV and sedan body-types, setting the stage for the multivariate modeling exercise that follows.

2.3. Stochastic Latent Constructs

This study considers the influence of three stochastic latent constructs on the main outcomes discussed above, the indicators for which are shown in Figure 1: *Green Lifestyle Propensity*, *Safety Consciousness*, and *Vehicle Status Perception*. A larger set of latent constructs was initially developed based on a comprehensive set of candidate indicators, with the final set of three latent constructs included in the model determined through a combination of Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), following extensive testing of a broader and overlapping set of potential constructs across alternative model specifications.

Green Lifestyle Propensity reflects the extent to which individuals prioritize sustainability and hold favorable attitudes toward the environment, capturing preferences for societal investment in sustainability efforts, general environmental values, and personal commitment to sustainability-oriented actions within the transportation sector. Responses to the underlying indicators (see Figure 1) reveal a moderate overall orientation toward environmentally-friendly behavior, though with considerable variation across items. A majority of respondents (32.6+20.8=53.4 percent) agree, at least somewhat, that they are committed to an environmentally-friendly lifestyle, and an even larger share (61.2 percent) agree that society should do more to encourage walking, bicycling, and public transportation use. However, actual reported behavior lags stated attitudes considerably: only 31.8 percent of respondents agree that they use less polluting means of transportation as much as possible, while 42.3 percent disagree with this statement, suggesting a gap between environmental values and travel behavior.

Safety Consciousness measures the degree to which individuals prioritize and express concern about transportation safety, both in their personal travel decisions and their broader policy preferences. This construct captures the belief that safety should be the primary focus of transportation investment, support for enforcement measures aimed at reducing dangerous driving behaviors, and personal comfort with retaining control over one's own travel safety. The indicators point to strong and fairly consistent safety consciousness across the sample. A substantial majority of respondents (71.2 percent) agree that the primary goal of transportation investment should be reducing crashes and improving safety, and a similar majority (68.3 percent) support the use of cameras to catch and stop drivers who speed, text, or drive under the influence. Respondents also express strong preference for personal control over safety, with 65.9 percent agreeing that they feel safer driving themselves rather than being driven by others.

Vehicle Status Perception captures the extent to which individuals view vehicles as a means of social signaling relative to viewing them primarily in functional terms; those scoring higher on this construct tend to see vehicles as markers of social status and favor ownership of luxury-oriented vehicles, while those scoring lower tend to emphasize the functional attributes of vehicles relative to their everyday travel needs. The underlying indicators suggest that functional considerations dominate status considerations for most respondents. An overwhelming majority (85.0 percent) agree that it is more important that their vehicle works well than what brand it is or

what it looks like, and a similarly large majority (85.0 percent) agree that owning a car is important to them, reflecting the continued centrality of vehicle ownership to daily life. By contrast, sentiment is far more mixed, and skews negative, on the status-signaling item: 47.5 percent of respondents disagree, at least somewhat, that they like the status that comes from owning a certain type of vehicle, compared to just 30.7 percent who agree, indicating that overt status signaling through vehicle choice is a minority preference within the sample.

The set of three latent constructs included in this study was developed based on insights derived from the theory of planned behavior (Ajzen, 1991) and social identity theory (Barth et al., 2016; Tajfel, 1978). The concept of vehicle status perception, in particular, aligns closely with social identity theory, which highlights the interdependence between individual preferences and identification with particular social groups, as perceived ingroup norms shape such preferences.

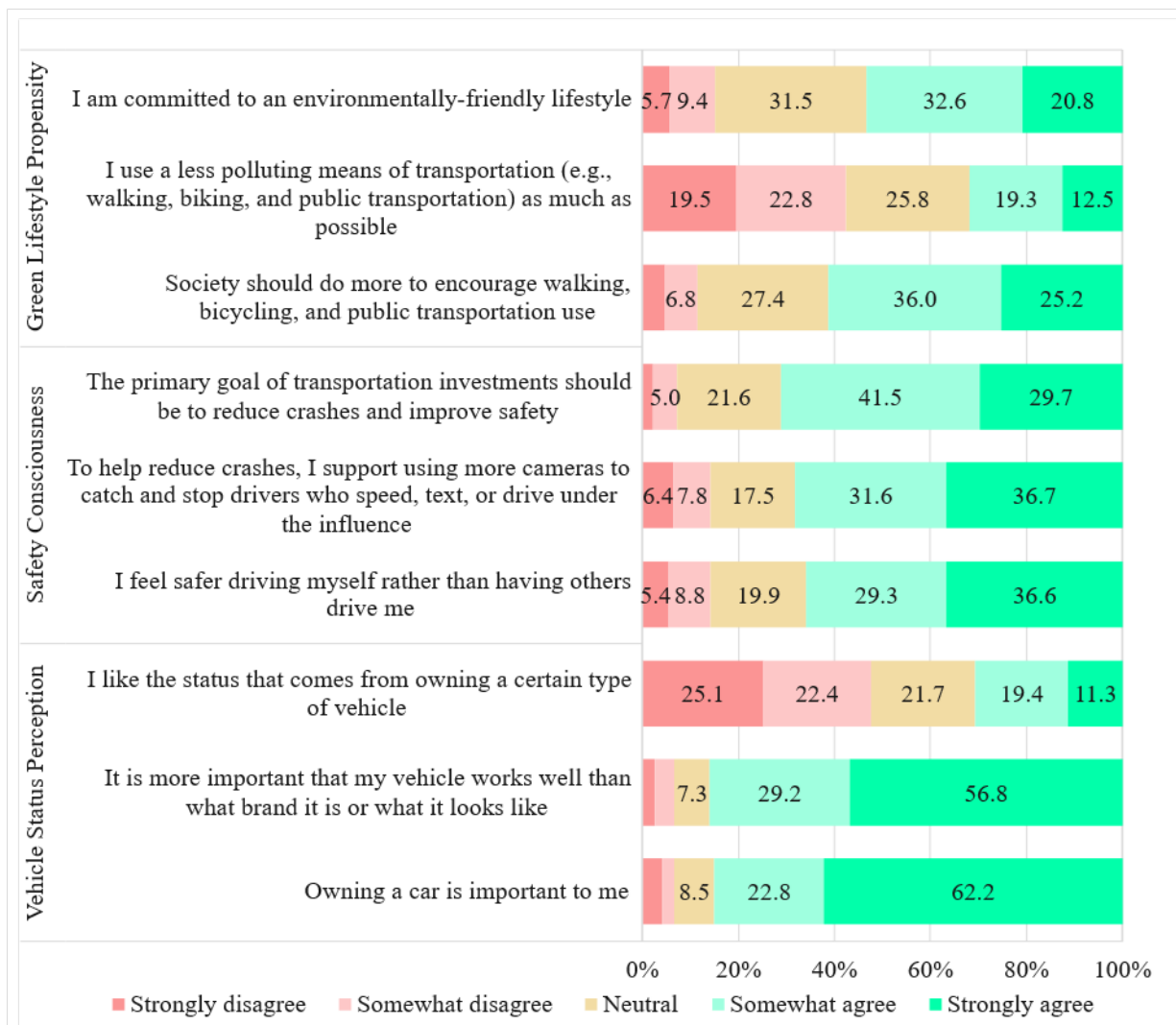


Figure 1. Agreement with Attitudinal Indicators Defining Latent Constructs

3. MODELING FRAMEWORK

Figure 2 presents the model structure, which constitutes a multivariate ordered probit (MORP) model of 13 vehicle ownership outcomes (described in Section 2.2) shown on the right side of the figure.

Although the ordinal outcomes considered here actually represent counts of vehicles owned by the household, both overall and within each body-type/fuel-type category, these outcomes are represented using an ordinal framework rather than a count framework. This is because an ordered response model is well suited to represent positive discrete count values with a limited range. Castro et al. (2012) and Bhat et al. (2015) demonstrate that a count model can be reformulated as a special case of a generalized ordered response model, providing the methodological basis for this approach. Given that very few households report five or more vehicles overall, the ordinal outcome for total vehicle ownership is limited to values ranging from zero through five. The counts of specific body-type/fuel-type combinations are similarly capped based on the maximum number of vehicles of each type held by any single household in the sample, as reported earlier in the lower portion of Table 1.

This ordinal framework offers two key advantages for the current application. It allows for efficient estimation of threshold parameters at each ordinal level, accommodating the high or low probability masses observed at certain levels for different outcomes. In addition, the framework supports estimation of the probability associated with any combination of count values across the outcome dimensions (that is, any combination of counts across body-type and fuel-type categories) within a single unified ordered response structure.

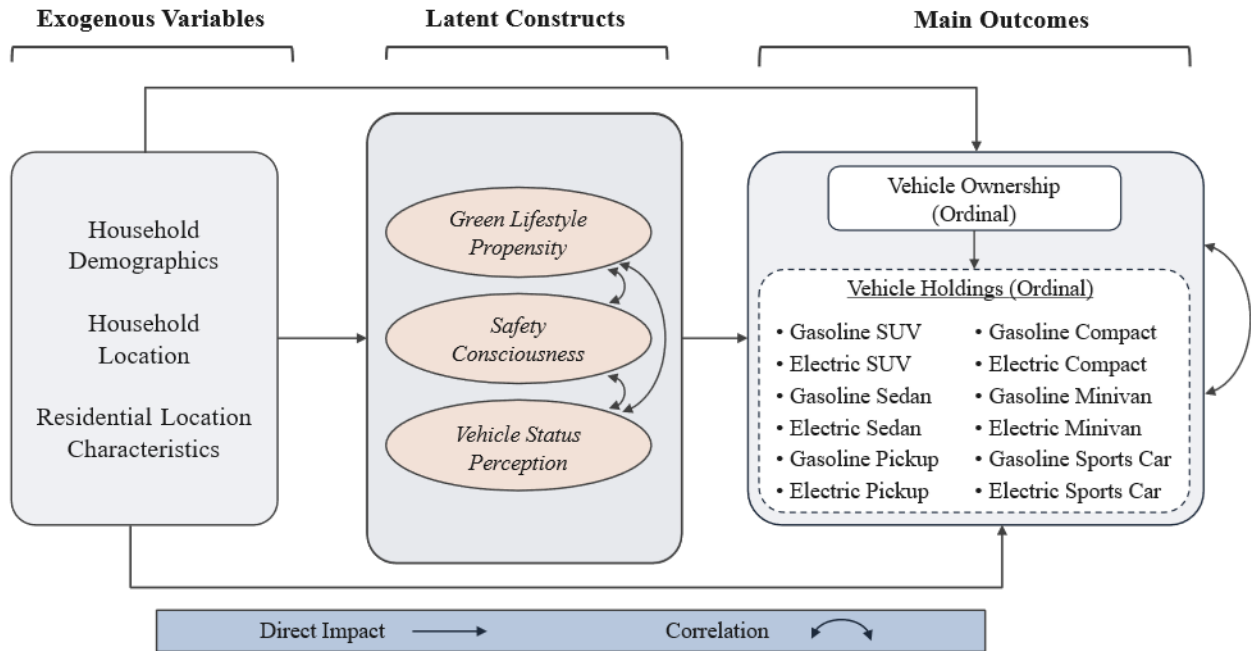


Figure 2. Model Framework

A significant methodological issue arises because not all combinations of ordered outcomes are feasible, since the sum of the vehicle counts across the 12 body-type/fuel-type dimensions must equal the household's total reported vehicle count. For example, it is not possible for a household to report owning one vehicle overall while simultaneously reporting ownership of

both a gasoline SUV and a gasoline sedan, nor is it possible for a household to report owning two vehicles overall while reporting ownership of a single gasoline SUV and no vehicles in any other body-type/fuel-type category.

Accounting for these infeasible outcome combinations requires an additional normalization in estimation. This is accomplished in two steps. First, the probability of each household's observed combination of outcomes is calculated relative to the full set of all possible combinations, including infeasible ones. This probability is then divided by the probability that the household selects any feasible combination of outcomes, again computed relative to the full set of combinations including infeasible ones. This normalization effectively removes infeasible combinations of the type described above from consideration, yielding the conditional likelihood of a household's observed combination of outcomes given that only a subset of all possible outcome combinations is feasible. The net result of this normalization is that the total number of vehicles owned by a household and the household's specific vehicle type preferences can be estimated jointly while maintaining internal consistency between these two dimensions. Within this joint framework, the influence of total vehicle ownership on preferences for specific vehicle types can also be estimated, after accounting for the correlation that also links these two sets of endogenous outcomes on the right side of Figure 2.

Household-level exogenous variables influence the main outcomes both directly and indirectly, with the indirect pathway operating through the three continuous latent constructs representing perceptions and lifestyle preferences, shown in the center of Figure 2 and discussed earlier in Section 2.3. Estimation proceeds through a two-stage process. In the first stage, the latent constructs are estimated based on their loadings on the set of indicators, together with a simultaneous linear regression of the latent constructs on the set of exogenous variables; this step effectively mirrors the structural equation model (SEM) component of Bhat's (2015) generalized heterogeneous data model (GHDM). In the second stage, the point estimates obtained for the continuous latent constructs are introduced as explanatory variables in the MORP model for the main outcomes, mirroring the measurement equation model (MEM) component of Bhat's (2015) GHDM.

This two-step estimator falls within the broader class of two-step optimization estimators, which are consistent and asymptotically normal under general conditions (Newey and McFadden, 1994). However, the asymptotic covariance matrix obtained in the second-stage MORP model must be corrected to properly account for the two-stage estimation approach, which we undertake using the procedure described by Terza (2016).

3.1. Mathematical Formulation of the Joint Modeling Framework

For the mathematical formulation of the first-stage component of the model, let q be an index for the household ($q = 1, 2, \dots, Q$) and let l be the index for the latent constructs ($l = 1, 2, \dots, L$). In the current context, $L = 3$, corresponding to the three latent constructs shown in the center of Figure 2. For the sake of simplicity, we will omit the index q , for the household, for the remainder of this presentation. Then, begin by labeling the underlying latent construct z_l^* . Let i be the index for the indicator variables ($i = 1, 2, \dots, I$), with $I = 9$ corresponding to the three indicators each for the three latent constructs. Also, let J be the number of categories for the ordinal indicators (in our case $J = 5$ for all ordinal indicator variables so there is no need to index by i) and let j be the corresponding index ($j = 1, 2, \dots, J$). Finally, for each ordinal indicator, let $\tilde{y}_i^*$ be the underlying

latent variable whose horizontal partitioning leads to the observed selection. Next, assume that the household chooses the a_i^{th} ordinal category for the indicator. Then, the factor analysis can be given by:

$$\tilde{y}_i^* = \tilde{\mathbf{d}}_i' \mathbf{z}^* + \tilde{\varepsilon}_i \quad (1)$$

with $\tilde{\psi}_{i,a_i-1} < \tilde{y}_i^* < \tilde{\psi}_{i,a_i}$, and where $\tilde{\mathbf{d}}_i$ is an $(L \times 1)$ vector of loadings of each latent construct on the ordinal indicator and $\mathbf{z}^* = (z_1^*, z_2^*, \dots, z_L^*)'$, the $\tilde{\psi}$ terms represent thresholds, and $\tilde{\varepsilon}_i$ represents the standard normal random error for the ordinal outcome. For each ordinal indicator, the thresholds must be ordered $\tilde{\psi}_{i,0} < \tilde{\psi}_{i,1} < \tilde{\psi}_{i,2} \dots < \tilde{\psi}_{i,J-1} < \tilde{\psi}_{i,J}$, with $\tilde{\psi}_{i,0} = -\infty$, $\tilde{\psi}_{i,1} = 0$, and $\tilde{\psi}_{i,J} = +\infty$. Let $\tilde{\boldsymbol{\psi}}_i = (\tilde{\psi}_{i,2}, \tilde{\psi}_{i,3}, \dots, \tilde{\psi}_{i,J-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_1', \tilde{\boldsymbol{\psi}}_2', \dots, \tilde{\boldsymbol{\psi}}_I)'$. Stack the I underlying continuous variables $\tilde{y}_i^*$ into an $(I \times 1)$ vector $\tilde{\mathbf{y}}^*$, and the I error terms $\tilde{\varepsilon}_i$ into an $(I \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define the $(I \times L)$ matrix $\tilde{\mathbf{d}} = (\tilde{\mathbf{d}}_1, \tilde{\mathbf{d}}_2, \dots, \tilde{\mathbf{d}}_I)$, and let $\mathbf{IDEN}_I$ be an identity matrix of dimension I that represents the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$ (note that the indicator propensities $\tilde{y}_i^*$ will still be correlated because of the correlations engendered through the stochastic latent constructs z_l^* , as will become clear from equation (5) below). Finally, stack the I lower thresholds for the household (based on their chosen level a_i of each indicator) into an $(I \times 1)$ vector $\tilde{\boldsymbol{\psi}}_{low}$ and the I upper thresholds into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the ordinal outcomes for the household may be written as:

$$\tilde{\mathbf{y}}^* = \tilde{\mathbf{d}} \mathbf{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\mathbf{y}}^* < \tilde{\boldsymbol{\psi}}_{up} \quad (2)$$

Next, to determine the effects of household demographics on these latent constructs, write each latent construct z_l^* as a function of covariates:

$$z_l^* = \boldsymbol{\alpha}_l' \boldsymbol{w} + \eta_l \quad (3)$$

where $\boldsymbol{w}$ is a $(D \times 1)$ vector of observed variables (excluding a constant), $\boldsymbol{\alpha}_l$ is a corresponding $(D \times 1)$ vector of coefficients, and η_l is a random error term. The error vector $\boldsymbol{\eta}$ is assumed to be standard normally distributed and captures the effects of unobserved factors that influence the stochastic latent constructs, after controlling for observed demographics. We also define the $(L \times D)$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \dots, \boldsymbol{\alpha}_L)'$, and the $(L \times 1)$ vector $\boldsymbol{\eta} = (\eta_1, \eta_2, \dots, \eta_L)'$. Thus, we may write Equation (1) in matrix form as:

$$\mathbf{z}^* = \boldsymbol{\alpha} \boldsymbol{w} + \boldsymbol{\eta} \quad (4)$$

In order to accommodate interactions among the unobserved latent variables, we allow a multivariate normal (MVN) correlation structure for $\boldsymbol{\eta}$. $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is an $(L \times L)$ correlation matrix.

Combining these two model components, we obtain the following reduced form equation:

$$\tilde{\mathbf{y}}^* = \tilde{\mathbf{d}} \mathbf{z}^* + \tilde{\boldsymbol{\varepsilon}} = \tilde{\mathbf{d}} (\boldsymbol{\alpha} \boldsymbol{w} + \boldsymbol{\eta}) + \tilde{\boldsymbol{\varepsilon}} = \tilde{\mathbf{d}} \boldsymbol{\alpha} \boldsymbol{w} + \tilde{\mathbf{d}} \boldsymbol{\eta} + \tilde{\boldsymbol{\varepsilon}} \quad (5)$$

Define $\mathbf{B} = \tilde{\mathbf{d}}\mathbf{a}\mathbf{w}$ and $\mathbf{\Omega} = \tilde{\mathbf{d}}\mathbf{\Gamma}\tilde{\mathbf{d}}' + \mathbf{IDEN}_I$. Then the multivariate joint distribution of the indicators of the latent constructs is $\tilde{\mathbf{y}}^* \sim \mathbf{MVN}_I(\mathbf{B}, \mathbf{\Omega})$.

Collect the set of parameters to be estimated in the first-stage into the vector $\delta_1 = [\text{Vech}(\mathbf{a}), \text{Vechup}(\mathbf{\Gamma}), \text{Vech}(\tilde{\mathbf{d}}), \tilde{\boldsymbol{\psi}}]$ where the operator $\text{Vech}(\cdot)$ vectorizes all the non-zero elements of the matrix/vector on which it operates and $\text{Vechup}(\cdot)$ vectorizes all the non-zero upper diagonal elements. Then the household-level likelihood function for the first-stage may be written as:

$$L(\delta) = \Pr \left[\tilde{\boldsymbol{\psi}}_{low} \leq \tilde{\mathbf{y}}^* \leq \tilde{\boldsymbol{\psi}}_{up} \right] = \int_{D_r} f_I(\mathbf{r} \mid \mathbf{B}, \mathbf{\Omega}) d\mathbf{r} \quad (6)$$

where the integration domain $D_r = \{\mathbf{r} : \tilde{\boldsymbol{\psi}}_{low} \leq \mathbf{r} \leq \tilde{\boldsymbol{\psi}}_{up}\}$ is the multivariate region of the elements of the $\tilde{\mathbf{y}}^*$ vector determined by the observed selections for the indicators. The likelihood function for the entire sample of household is obtained as the product of the household-level likelihood functions.³ Finally, based on the estimates for the first-stage model, we estimate the point-values for the continuous latent constructs for each household. That is, we construct $\hat{z}_i^* = \hat{\mathbf{a}}_i' \mathbf{w}$ where $\hat{\mathbf{a}}$ are the estimated coefficients for the first stage model. These estimated point-values are then used for the estimation of the main outcomes in the second-stage, as discussed next.

For the second-stage model component, consider N ordinal outcomes and denote the index for the ordinal outcomes as n ($n = 1, 2, \dots, N$). In our current context, $N = 13$ corresponding to a single dimension representing the number of vehicles and twelve additional dimensions representing the body-type/fuel-type combinations. Then, let K_n be the number of categories for the k^{th} ordinal outcome ($K_n \geq 2$) and let k_n be the corresponding index ($k_n = 0, 1, 2, \dots, K_n - 1$).⁴ Also, for each ordinal outcome, following the same framework as above, let $\tilde{y}_n^*$ be the underlying latent variable whose horizontal partitioning leads to the observed outcome $\tilde{y}_n$. Next, assume that the household chooses the ordinal category c_n . Then, we can apply the usual ordered response formulation, for the household, to write:

$$\tilde{y}_n^* = \tilde{\boldsymbol{\gamma}}_n' \mathbf{x} + \tilde{\mathbf{b}}_n' \hat{\mathbf{z}}^* + \tilde{\varepsilon}_n \quad (7)$$

with $\tilde{\boldsymbol{\psi}}_{n, c_n} < \tilde{y}_n^* < \tilde{\boldsymbol{\psi}}_{n, c_n + 1}$, and where $\mathbf{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous variables (included in a recursive fashion), $\tilde{\boldsymbol{\gamma}}_n$ is a vector of corresponding coefficients to be estimated, $\tilde{\mathbf{b}}_n$ is an $(L \times 1)$

³The complete model system is estimated using Bhat's (2018) matrix-based approximations to the multivariate normal cumulative distribution function. Also, see Bhat (2015) for additional discussion of the identifiability of all elements of the δ_1 vector.

⁴Based on Table 1, $K_1 = 6$ for the overall vehicle ownership dimension, $K_2 = 5$ for gasoline SUVs, $K_3 = 3$ for electric SUVs, $K_4 = 5$ for gasoline sedans, $K_5 = 3$ for electric sedans, $K_6 = 4$ for gasoline pickups, $K_7 = 2$ for electric pickups, $K_8 = 4$ for gasoline compact cars, $K_9 = 3$ for electric compact cars, $K_{10} = 3$ for gasoline minivans, $K_{11} = 2$ for electric minivans, $K_{12} = 4$ for gasoline sports cars, and $K_{13} = 2$ for electric sports cars.

vector of loadings of each latent construct on the ordinal outcome (using the estimated point-values $\hat{z}^*$), the $\tilde{\psi}$ terms represent thresholds to be estimated, and $\tilde{\varepsilon}_n$ represents the standard normal random error for the ordinal outcome. Again, for each ordinal outcome, the thresholds must be ordered $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \dots < \tilde{\psi}_{n,K_n-1} < \tilde{\psi}_{n,K_n}$, with $\tilde{\psi}_{n,0} = -\infty$ and $\tilde{\psi}_{n,K_n} = +\infty$. Let $\tilde{\psi}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3}, \dots, \tilde{\psi}_{n,K_n-1})'$ and $\tilde{\psi} = (\tilde{\psi}'_1, \tilde{\psi}'_2, \dots, \tilde{\psi}'_N)'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{\mathbf{y}}^*$, and the N error terms $\tilde{\varepsilon}_n$ into an $(N \times 1)$ vector $\tilde{\mathbf{\varepsilon}}$. Define the $(N \times A)$ matrix $\tilde{\boldsymbol{\gamma}} = (\tilde{\boldsymbol{\gamma}}_1, \tilde{\boldsymbol{\gamma}}_2, \dots, \tilde{\boldsymbol{\gamma}}_N)'$ and the $(N \times L)$ matrix $\tilde{\mathbf{b}} = (\tilde{\mathbf{b}}_1, \tilde{\mathbf{b}}_2, \dots, \tilde{\mathbf{b}}_N)$. Then, stack the N lower thresholds for the decision-maker $\tilde{\psi}_{n,c_n}$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{\psi}}_{low}$ and the N upper thresholds $\tilde{\psi}_{n,c_n+1}$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Finally, define an $(N \times N)$ matrix $\boldsymbol{\Sigma}$ representing the correlation matrix of $\tilde{\mathbf{\varepsilon}}$, which is multivariate normally distributed with a mean vector of zeros and correlation matrix given by:

$$\boldsymbol{\Sigma} = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \dots & \rho_{1I} \\ \rho_{12} & 1 & \rho_{23} & \dots & \rho_{2I} \\ \rho_{13} & \rho_{23} & 1 & \dots & \rho_{3I} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{1I} & \rho_{2I} & \rho_{3I} & \dots & 1 \end{pmatrix} \quad (8)$$

The off-diagonal terms of $\boldsymbol{\Sigma}$ capture error correlations among the underlying latent propensities of the endogenous outcomes, accommodating the presence of unobserved variables that jointly influence multiple outcomes. Then, in matrix form, the latent propensities underlying the observed multivariate outcome for the household should satisfy:

$$\tilde{\mathbf{y}}^* = \tilde{\boldsymbol{\gamma}}\mathbf{x} + \tilde{\mathbf{b}}\hat{\mathbf{z}}^* + \tilde{\mathbf{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\mathbf{y}}^* < \tilde{\boldsymbol{\psi}}_{up} \quad (9)$$

Now, define a vector $\boldsymbol{\delta}_2$ that collects the parameters to be estimated: $\boldsymbol{\delta}_2 = [\text{Vech}(\tilde{\boldsymbol{\gamma}}), \text{Vech}(\tilde{\mathbf{b}}), \tilde{\boldsymbol{\psi}}, \boldsymbol{\vartheta}, \text{Vechup}(\boldsymbol{\Sigma})]$. Then the multivariate joint distribution of the outcomes is $\tilde{\mathbf{y}}^* \sim \text{MVN}_N(\tilde{\boldsymbol{\gamma}}\mathbf{x} + \tilde{\mathbf{b}}\hat{\mathbf{z}}^*, \boldsymbol{\Sigma})$.

Finally, as noted previously, not all combinations of outcomes are possible. First, when $\tilde{y}_1 = 0$, corresponding to a household owning zero vehicles, there are no body-type/fuel-type ownership dimensions that are relevant, so the model collapses to a single univariate ordered outcome for vehicle ownership. Second, when $\tilde{y}_1 > 0$, the counts of body-type/fuel-type combinations must sum to the total count of vehicles. Therefore, we normalize the likelihood function based on the possible combinations of outcomes. To do so, define the set of possible

outcome combinations as $\mathbf{G} = \left\{ \mathbf{g} = (g_1, g_2, \dots, g_N) \in K_1 \times \dots \times K_N \mid g_1 = \sum_{n=2}^N g_n \right\}$, where each element

$\mathbf{g}$ is a $(N \times 1)$ vector indicating the ordinal levels of each outcome in one possible outcome combination. Vectors of upper and lower thresholds for this possible outcome combination $\mathbf{g}$ can be defined, similar to the vectors defined for the observed household (as described above) as $\tilde{\boldsymbol{\psi}}_{g,low}$ and $\tilde{\boldsymbol{\psi}}_{g,up}$. Thus, the household-level likelihood function may be written as:

$$L(\delta) = \frac{\Pr \left[\tilde{\psi}_{low} \leq \tilde{\mathbf{y}}^* \leq \tilde{\psi}_{up} \right]}{\sum_{g \in G} \Pr \left[\tilde{\psi}_{g,low} \leq \tilde{\mathbf{y}}^* \leq \tilde{\psi}_{g,up} \right]} = \frac{\int_{D_r} f_N(\mathbf{r} | \tilde{\gamma}\mathbf{x} + \tilde{\mathbf{b}}\mathbf{z}^*, \Sigma) d\mathbf{r}}{\sum_{g \in G} \int_{D_g} f_N(\mathbf{r} | \tilde{\gamma}\mathbf{x} + \tilde{\mathbf{b}}\mathbf{z}^*, \Sigma) d\mathbf{r}} \quad (10)$$

where the integration domain $D_r = \{\mathbf{r} : \tilde{\psi}_{low} \leq \mathbf{r} \leq \tilde{\psi}_{up}\}$ is the multivariate region of the elements of the $\tilde{\mathbf{y}}^*$ vector determined by the observed ordinal outcomes and the domain $D_r = \{\mathbf{r} : \tilde{\psi}_{low} \leq \mathbf{r} \leq \tilde{\psi}_{up}\}$ is the multivariate region of the elements of the $\tilde{\mathbf{y}}^*$ vector determined by the specific possible combination of outcomes $\mathbf{g}$. The likelihood function for the entire sample of decision-makers is obtained as the product of the household-level likelihood functions. Finally, as mentioned earlier, the covariance matrix of the parameters obtained in the second stage of estimation must be corrected to account for the two-stage estimation approach applied. This correction is performed using the methods outlined by Terza (2016).

4. MODEL ESTIMATION RESULTS

Model estimation results are presented in this section. Section 4.1 discusses the effects of exogenous variables on the latent constructs. Section 4.2 discusses the effects of exogenous variables and latent constructs on the main outcomes as well as the endogenous effects of the overall number of vehicles on the propensities for each body-type/fuel-type combination and the correlations among the outcomes. Finally, Section 4.3 presents an assessment of overall model fit.

4.1. Latent Constructs Estimation Results

Results for the structural equations model (SEM) component, capturing the effects of exogenous variables on the three latent constructs, are presented in the upper portion of Table 2.

Household income has a clear effect on vehicle status perception. Households earning \$100,000 or more score higher on this construct than lower-income households. This finding is consistent with a greater tendency toward conspicuous consumption of luxury goods among higher-income households, who may feel less pressure to prioritize the functional attributes of a vehicle (Sovacool and Axsen, 2018). Educational attainment shapes all three latent constructs. Those with a bachelor's degree or a graduate degree exhibit a higher green lifestyle propensity than those with less education, with the effect strengthening at the graduate level, conforming to prior findings that higher levels of education are associated with greater awareness of environmental degradation and a stronger sense of agency in mitigating it (Liu et al., 2020). Those with a graduate degree also exhibit higher safety consciousness, consistent with evidence that more educated individuals are less likely to engage in risky driving behaviors such as driving under the influence or without a seatbelt (Cutler and Lleras-Muney, 2010). At the same time, individuals with a graduate degree score modestly lower on vehicle status perception, placing relatively greater emphasis on vehicle functionality. That is, higher education shapes spending habits, shifting emphasis toward the functional attributes of major purchases such as vehicles rather than their social signaling value (Memushi, 2014; Jaikumar and Sharma, 2021).

Race and ethnicity also shape these lifestyle preferences. Non-White and Hispanic individuals exhibit a greater green lifestyle propensity than White and non-Hispanic individuals, respectively. Non-White individuals additionally exhibit higher safety consciousness. Both non-White and Hispanic individuals score lower on vehicle status perception. These patterns are consistent with expectations and past evidence. Non-White and Hispanic individuals are

disproportionately affected by environmental degradation (Macias, 2016) and by transportation safety concerns (Haddad et al., 2023), while also tending to hold consumption values more closely aligned with functional considerations in major purchases such as vehicles and homes (Charron-Chénier et al., 2017).

Housing type is similarly influential. Apartment dwellers, relative to those living in single-family homes, exhibit a higher green lifestyle propensity. This likely reflects a self-selection effect, as apartment living tends to be less land-consumptive and situated closer to amenities, reducing travel-related emissions (Robbennolt et al., 2024). Apartment residents also score lower on vehicle status perception, consistent with a broader set of preferences among this group that favor functional considerations over status-oriented consumption. When it comes to household composition, single-male-adult households (compared to all multi-adult households) exhibit lower safety consciousness and higher vehicle status perception, while single-female-adult households, by contrast, score lower on vehicle status perception (that is, they place relatively greater emphasis on vehicle functionality).

The presence of children in the household is associated with a higher green lifestyle propensity and higher safety consciousness. The former has been attributed to legacy motives, whereby parents place greater weight on long-term environmental outcomes (Shrum et al., 2023). Life-cycle stage also plays a role. Households with a retired adult exhibit a lower green lifestyle propensity than households without a retired adult, suggesting that retired and later-life-cycle households place less emphasis on environmentally friendly behavior overall. The presence of a retired adult is also associated with a somewhat higher vehicle status perception. The age of the oldest household member shows a related but distinct pattern: relative to the youngest age category, all older age groups exhibit lower vehicle status perception, with the magnitude of this effect generally increasing with age. This suggests that as individuals age, functional considerations become increasingly important relative to status considerations in vehicle preferences, even as retirement status itself is associated with a modest counteracting shift toward status. Households in which the oldest member is aged 75 years or over exhibit higher safety consciousness. These patterns may reflect a life-course shift toward comfort- and safety-related features with the onset of age-related mobility limitations and changes in daily mobility needs, together with a changing social identity around vehicle ownership that often accompanies retirement (Bordia et al., 2020).

TABLE 2 Determinants of Latent Variables and Loadings on Indicators

Explanatory variables (base category)		Structural Equations Model Component					
		Green Lifestyle Propensity		Safety Consciousness		Vehicle Status Perception	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Household income (< \$100,000)	\$100,000 or more	—		—		0.25	6.01
Education (less than a bachelor's degree)	Bachelor's degree(s)	0.20	6.05	—		—	
	Graduate degree(s)	0.37	8.95	0.12	2.62	-0.08	-1.91
Race (White)	Non-White	0.36	12.14	0.12	3.90	-0.12	-3.56
Ethnicity (not Hispanic)	Hispanic	0.16	4.71	—		-0.06	-2.01
Home type (single family home)	Apartment	0.20	5.63	—		-0.11	-2.49
Household composition (multi-adult household)	Single male adult	—		-0.09	-1.77	0.13	1.95
	Single female adult	—		—		-0.12	-1.85
Presence of children (none)	One or more	0.19	6.54	0.15	4.68	—	
Presence of retired adults (none)	One or more	-0.07	-3.43	—		0.07	3.70
Age of eldest household member (18 to 44 years)	45 to 64 years	-0.12	-4.12	—		-0.11	-3.10
	65 to 74 years	-0.13	-3.17	—		-0.16	-3.56
	75 years or older	-0.15	-2.78	0.08	2.07	-0.17	-2.95
Attitudinal indicators		Loadings of Latent Variables on Indicators (Measurement Equations Model Component)					
I am committed to an environmentally-friendly lifestyle		0.73	35.91	—		—	
I use a less polluting means of transportation (e.g., walking, biking, and public transportation) as much as possible		0.83	29.99	—		—	
Society should do more to encourage walking, bicycling, and public transportation use		0.57	29.35	—		—	
The primary goal of transportation investments should be to reduce crashes and improve safety		—		0.64	22.71	—	
To help reduce crashes, I support using more cameras to catch and stop drivers who speed, text, or drive under the influence		—		0.52	26.16	—	
I feel safer driving myself rather than having others drive me		—		0.80	22.88	—	
I like the status that comes from owning a certain type of vehicle		—		—		0.62	21.89
It is more important that my vehicle works well than what brand it is or what it looks like		—		—		-0.71	-21.75
Owning a car is important to me		—		—		0.56	22.75
Correlations between latent constructs							
Green Lifestyle Propensity		1.00	—	0.27	28.02	0.16	14.01
Safety Consciousness				1.00	—	-0.14	-13.42
Vehicle Status Perception						1.00	—

Note: Coeff. = coefficient; “—” = not statistically significant at the 90% confidence level or not applicable for the latent construct.

The loadings of the three latent constructs on their respective attitudinal indicators, along with the correlations among the latent constructs, are presented in the lower portion of Table 2. All indicator loadings take the expected sign, consistent with the wording of the underlying attitudinal statements included in the survey. The correlation structure among the latent constructs reveals several notable patterns. Green lifestyle propensity and safety consciousness are strongly positively correlated. This is intuitive, as individuals who are more civically minded and socially conscious are likely to score higher on both dimensions simultaneously. Green lifestyle propensity and vehicle status perception exhibit a smaller, though still positive, correlation, suggesting a degree of alignment between environmental attitudes and status-oriented vehicle preferences; this may reflect the fact that some green vehicle purchases serve as a form of social signaling of environmental values, rather than being motivated purely by personal sustainability goals. Finally, safety consciousness and vehicle status perception are negatively correlated. This is also intuitive, as individuals with a stronger safety orientation likely prioritize the functional, safety-related attributes of a vehicle over considerations of status and social signaling.

4.2. Main Estimation Results

The main estimation results are presented in Table 3 and discussed in the remainder of this subsection. All effects discussed in this section refer to effects on the underlying propensities for each ordinal outcome, and should be interpreted as general (average) tendencies. Of course, there are always deviations from these general tendencies.

4.2.1. Effects of Latent Constructs

The three latent constructs shape both the size and composition of the household vehicle fleet, though in distinct ways. Households with a higher green lifestyle propensity have a lower vehicle ownership propensity, consistent with a lower overall level of consumption. These households also lean toward electric vehicles across nearly every body-type, while avoiding gasoline SUVs in particular, likely reflecting a perception of SUVs as especially environmentally harmful.

Safety-conscious households, by contrast, tend to lean toward a higher ownership propensity. This suggests a greater reliance on personal vehicle travel to avoid riskier modes such as walking or cycling. These households also have a particularly elevated propensity for gasoline SUVs compared with other body-types, while showing less interest in gasoline pickups and in compact cars of either fuel-type. This pattern is consistent with the greater perceived safety of larger vehicles relative to smaller ones (Thomas and Walton, 2008).

Vehicle status perception has little bearing on total fleet size but shapes fleet composition considerably. Households that view vehicles primarily as status symbols gravitate toward sports cars (both gasoline and electric). Households that instead emphasize functionality have heightened propensities for sedans, pickup trucks, and minivans.

4.2.2. Effects of Household Demographics

The effects discussed in this section represent direct effects of household demographics on the latent propensities underlying the main outcomes, after accounting for the indirect effects operating through the three latent constructs.

Income remains a central determinant of vehicle ownership. Higher-income households have a higher vehicle ownership propensity, favor gasoline SUVs over other body-types, and have consistently higher propensities for electric vehicles across nearly every body-type. This latter pattern underscores the continued role of purchase price as a barrier to broader EV adoption

(Robbennolt et al., 2025b). Educational attainment shows a related but distinct pattern. Those with higher levels of educational attainment have higher vehicle ownership propensities and are more likely to favor sedans, but lean away from gasoline pickups or minivans, a pattern plausibly linked to the more urban, commute-oriented residential locations typical of higher-education households (see Booi and Boterman, 2020).

Race and ethnicity shape both fleet size and composition. Non-White households have a lower propensity for vehicle ownership, as well as a lower propensity for gasoline SUVs, pickup trucks, and compact cars, but a higher propensity for gasoline sedans and sports cars – a pattern consistent with prior literature (Vyas et al., 2012; Molloy et al., 2024). Hispanic households, by contrast, own more vehicles overall and show a greater propensity for gasoline pickup trucks and compact cars.

Housing tenure and type matter as well. Apartment dwellers and renters both have a lower vehicle ownership propensity overall, plausibly reflecting smaller household sizes and more urban living with more limited and less secure parking access (NHMC, 2022). Renters exhibit markedly lower propensities for electric vehicles, consistent with the reduced control renters have over installing home charging infrastructure (Hoogland and Hardman, 2025). Apartment dwellers also show reduced interest in SUVs, minivans, and sports cars specifically, likely reflecting the practical challenges of parking larger vehicles in denser settings, along with smaller typical household sizes (Bhat and Sen, 2005; Cao et al., 2006).

Household composition reveals both life-stage and gender-related patterns. Single-adult households have lower vehicle ownership propensities compared with larger households, while the presence of children increases vehicle ownership propensity, except among single-parent households. Single adults (compared with all multi-adult households) show less interest in gasoline minivans; single women are less interested in gasoline pickups and sports cars; while single men show a distinct affinity for electric pickups and sports cars. These differences suggest that gender remains closely tied to vehicle preferences even after accounting for latent lifestyle constructs (Choo and Mokhtarian, 2004; Pazhoohi and Kingstone, 2022). Roommate households lean toward sedans and compact cars, consistent with greater affordability needs at an earlier life stage, while extended-family households favor SUVs and sedans, likely reflecting the flexibility these vehicles offer larger households that may have differing needs (see Khan and Habib, 2021). Households with children also show somewhat greater interest in electric vehicles overall, though this pattern is muted among single parents.

Households with retired adults and those with more employed adults both tend toward higher overall vehicle ownership propensities, though for different vehicle types. Retired-adult households show a stronger preference for gasoline SUVs, pickup trucks, and compact cars, consistent with older adults' preference for the safety, comfort, and easier maneuverability these vehicles offer (Cox and Cicchino, 2022). Households with more employed adults, by contrast, show broad demand across nearly all body-types and fuel-types, gasoline and electric alike, reflecting both functional commuting needs and greater purchasing power for less utilitarian vehicles such as sports cars (Khan and Habib, 2021).

Finally, life-cycle stage, captured by the age of the oldest household member, shows little effect on total fleet size but does shape fleet composition. Preferences for gasoline minivans rise with age, while propensities for gasoline sedans are particularly pronounced among the oldest households (75 and older). Electric vehicle preferences decline modestly with age, after accounting for the indirect effect of age through green lifestyle propensity. Finally, propensities for gasoline SUVs peak in the middle-age categories (45 to 74), while a distinct preference for gasoline pickups

is concentrated among those aged 45 to 64, plausibly reflecting a desire for flexibility, comfort, storage capacity, and ease of use as households age (Cox and Cicchino, 2022).

4.2.3. Effects of Household Location

Several built-environment characteristics of the household's residential location shape both fleet size and composition. Rural households show a distinct compositional preference, favoring gasoline pickup trucks while showing less interest in gasoline SUVs and gasoline sedans relative to urban households.

Interestingly, households in areas with greater land-use diversity exhibit a greater vehicle ownership propensity overall, suggesting that mixed-use development does not necessarily translate into reduced vehicle dependence. Car network density is associated with a greater preference for sedans, both gasoline and electric, relative to other (larger) body-types. This finding highlights the propensity of households to own smaller vehicles in denser urban areas that tend to experience greater levels of congestion.

Walkability and transit accessibility both have a negative relationship with overall vehicle ownership propensity, underscoring the importance of infrastructure supporting these alternative modes as a means of reducing auto dependence (although self-selection effects are also likely at play). At the level of specific vehicle types, these built-environment measures show a more nuanced pattern. Transit accessibility, in particular, is associated with a notably higher propensity for electric compact car ownership, alongside a lower propensity for gasoline sedan and gasoline compact car ownership, suggesting some degree of compatibility in household preferences for access to transit and electric vehicle adoption.

Finally, census division indicators are included to control for broader regional variation in vehicle preferences across the United States. Overall vehicle ownership propensities are lower in the Middle Atlantic and South Atlantic divisions and higher in the West North Central and Mountain divisions, relative to the reference divisions. Additional regional variation is evident in vehicle body-type and fuel-type preferences across divisions, though these differences are likely capturing unknown unobserved factors and are therefore not discussed in further detail.

4.2.4. Endogenous Effects

As mentioned above, modeling these 13 outcomes jointly makes it possible to directly estimate the effect of total vehicle ownership on preferences for individual vehicle types within this package decision framework. This is accomplished after accounting for correlations among the endogenous outcomes (as discussed in the following section), which capture unobserved household-level factors that might otherwise make some households more likely to have larger vehicle fleets while also being more drawn to specific vehicle types. In other words, the correlations in the model account for these unobserved tendencies; thus, the endogenous effect of total vehicle ownership on specific vehicle type preferences can be interpreted as a structural direct effect, after controlling for jointness in choice among the outcomes.

Electric vehicles, across nearly all body-types, are markedly more common among households with larger vehicle fleets (of three or more vehicles) than among households with fewer vehicles. This is an important and noteworthy result. It suggests that considerable hesitancy remains regarding the ability of electric vehicles to fully substitute for gasoline vehicles. Instead, electric vehicles appear to be adopted first among households with larger fleets, who can rely on their other vehicles for trips that are less conducive to being accomplished using electric vehicles.

This suggests that electric vehicle adoption campaigns and incentives may yield greater benefits if targeted towards households with larger vehicle fleets.

Gasoline pickup trucks and sports cars follow a similar pattern, appearing more frequently among households with larger vehicle fleets. This is an intuitive result, as both vehicle types are relatively specialized for specific trip types and may be viewed as less practical primary vehicles among households with only one or two vehicles.

4.2.5. Thresholds and Correlation Terms

The threshold parameters shown at the bottom of Table 3 are estimated to match the observed proportion of households at each level of every ordered outcome. They do not carry a substantive behavioral interpretation, though the markedly high threshold terms for many of the electric vehicle propensities do reflect the relative overall rarity of electric vehicle ownership (as discussed in aggregate in Section 2.2).

The correlation terms capture the influence of unobserved factors affecting multiple outcomes simultaneously. Total vehicle ownership is positively correlated with ownership of nearly every gasoline vehicle type, suggesting that unobserved factors beyond those captured by the latent constructs lead some households toward both a general preference for gasoline vehicles and a preference for owning more vehicles overall.

Negative correlations among several of the vehicle type dimensions point to combinations of vehicle preferences that pull in opposite directions after accounting for observed characteristics. The correlation between gasoline SUV and gasoline sedan holdings, for example, is significantly negative (-0.37 , $t = -6.62$). This suggests that households with a preference for larger vehicle body-types, reflecting space or capacity needs not otherwise captured in the model, are correspondingly less likely to hold a preference for smaller vehicle types such as sedans. This correlation points to an underlying, unobserved taste for vehicle size that pulls preferences in opposite directions across these two relatively common body-types. Other correlation terms may be interpreted in a similar manner; a detailed explanation of every correlation term is omitted in the interest of brevity. The key point to note is that the model framework accounts for such correlated unobserved factors, thus ensuring that direct effects captured in the model estimation results represent true effects as opposed to spurious effects that may be confounded by unobserved factors.

TABLE 3 Estimation Results of the Main Outcome Model Components

Explanatory Variables (base category)		Number of Vehicles		Gasoline SUV		Electric SUV		Gasoline Sedan		Electric Sedan	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Latent Constructs											
Green Lifestyle Propensity		-0.26	-8.76	-0.18	-5.48	0.42	5.63	0.12	4.35	0.31	4.19
Safety Consciousness		0.10	2.82	0.09	2.31	—		—		—	
Vehicle Status Perception		—		—		—		-0.19	-3.98	—	
Demographics											
Household Income (less than \$25,000)	\$25,000 - \$49,999	0.31	4.97	—		—		—		—	
	\$50,000 - \$99,999	0.56	9.10	0.23	3.94	—		—		0.47	2.03
	\$100,000 - \$149,999	0.69	9.32	0.37	5.83	0.53	4.37	—		0.50	2.10
	\$150,000 - \$199,999	0.83	9.04	0.37	5.83	0.53	4.37	—		0.50	2.10
	\$200,000 or more	1.03	9.29	0.49	4.21	0.75	3.69	—		0.50	2.10
Educational Attainment (less than high school)	High school diploma	0.31	2.73	—		—		—		—	
	Undergraduate degree	0.29	2.49	—		—		0.07	1.75	0.37	2.50
	Graduate degree	0.29	2.49	—		0.22	1.71	0.13	2.30	0.49	3.00
Race (white)	Non-white	-0.07	-1.85	-0.11	-2.30	—		0.08	1.92	—	
Ethnicity (not Hispanic)	Hispanic	0.10	2.07	—		—		—		—	
Home Type (single-family)	Apartment	-0.30	-4.92	-0.13	-1.79	-0.27	-1.76	—		—	
Tenure Type (own)	Rent	-0.23	-4.65	—		-0.33	-2.26	0.16	3.09	-0.48	-2.54
Household Composition (Couple)	Single male adult	-0.53	-6.09	-0.45	-4.36	—		-0.08	-1.72	—	
	Single female adult	-0.64	-6.56	-0.27	-2.61	-0.34	-1.79	-0.08	-1.72	-0.52	-1.86
	Single parent	-0.33	-2.56	—		—		—		—	
	Roommate household	—		-0.14	-2.24	—		0.12	1.73	0.25	1.67
	Extended family	0.21	4.38	0.09	2.31	—		0.23	4.26	—	
Presence of children (no)	Yes	0.10	1.85	—		0.17	1.65	-0.08	-1.67	0.22	1.86
Presence of retired adults (no)	Yes	0.30	4.97	0.09	2.30	—		—		—	
Number of employed adults		0.13	3.77	0.10	3.46	0.08	1.97	0.05	1.95	—	
Age of eldest household member (18-44)	45-64	—		0.07	1.86	-0.33	-2.70	—		-0.23	-1.98
	65-74	—		0.10	1.65	-0.45	-2.67	—		-0.31	-1.95
	75+	—		—		-0.45	-2.67	0.12	1.73	-0.31	-1.95
Household Location											
Population density (urban)	Rural	—		-0.13	-1.71	—		-0.20	-2.99	—	
Land-use diversity		0.35	2.36	—		—		—		—	
Car network density		—		—		—		0.03	1.73	0.04	1.92
Walkability		-0.46	-4.06	-0.03	-3.16	0.02	1.99	—		0.02	1.67
Transit accessibility		-0.02	-3.43	—		—		-0.37	-2.97	—	
Census division (New England, East South Central, or Pacific)	Middle Atlantic	-0.21	-3.13	0.17	2.36	—		—		—	
	East North Central	—		0.15	2.11	-0.26	-1.78	-0.13	-2.00	—	
	West North Central	0.11	2.18	0.12	1.71	—		—		—	
	South Atlantic	-0.11	-1.91	—		—		—		—	
	West South Central	—		—		—		-0.11	-1.75	—	
Mountain		0.08	1.69	—		—		-0.13	-1.74	—	
Endogenous Effects											
Number of Vehicles (0-2)	3 or more	—		—		0.18	1.86	—		0.28	1.93
Thresholds											
0 1		-1.06	-7.11	0.10	0.92	2.52	10.04	0.52	6.91	2.97	8.98
1 2		0.85	6.05	1.50	13.28	2.84	10.62	1.85	21.92	3.41	12.21
2 3		2.16	15.25	2.12	17.62	3.01	12.67	2.27	25.45	—	
3 4		2.94	20.15	2.49	19.65	—		2.93	29.65	—	
4 5		3.64	23.55	—		—		—		—	
Correlations											
Number of Vehicles		—		0.38	7.81	—		0.34	6.92	—	
Gasoline SUV		—		—		-0.13	-2.31	-0.37	-6.62	-0.15	-2.80
Gasoline Pickup		—		—		—		-0.16	-1.82	—	
Gasoline Compact		—		—		—		-0.13	-2.13	—	
Gasoline Minivan		—		—		—		—		—	

TABLE 3 (Continued)

Explanatory Variables (base category)		Gasoline Pickup		Electric Pickup		Gasoline Compact		Electric Compact	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Latent Constructs									
Green Lifestyle Propensity		—		0.43	2.90	—		0.29	2.65
Safety Consciousness		-0.08	-1.81	—		-0.12	-2.67	-0.21	-2.01
Vehicle Status Perception		-0.12	-1.85	—		—		—	
Demographics									
Household income (less than \$25,000)	\$25,000 - \$49,999	—		—		—		—	
	\$50,000 - \$99,999	—		0.51	1.74	—		—	
	\$100,000 - \$149,999	—		0.59	1.70	—		0.41	2.29
	\$150,000 - \$199,999	—		0.59	1.70	—		0.41	2.29
	\$200,000 or more	—		0.59	1.70	—		0.45	1.84
Educational attainment (less than high school)	High school diploma	—		—		—		—	
	Undergraduate degree	-0.22	-3.02	—		—		—	
	Graduate degree	-0.32	-3.59	—		—		—	
Race (White)	Non-White	-0.17	-2.54	—		-0.07	-1.69	—	
Ethnicity (not Hispanic)	Hispanic	0.17	2.40	—		0.10	1.86	—	
Home Type (single-family)	Apartment	-0.35	-3.39	—		—		—	
Tenure Type (own)	Rent	-0.22	-2.99	—		—		-0.39	-1.90
Household composition (couple)	Single male adult	—		0.45	1.70	—		—	
	Single female adult	-0.67	-5.06	—		—		—	
	Single parent	-0.27	-1.71	—		—		—	
	Roommate household	—		—		0.16	1.70	0.42	1.84
	Extended family	-0.17	-2.44	—		0.10	1.63	—	
Presence of children (no)	Yes	—		0.70	1.80	-0.08	-1.77	0.20	1.77
Presence of retired adults (no)	Yes	0.16	3.27	—		0.07	1.69	—	
Number of employed adults		0.16	4.40	—		0.08	2.24	—	
Age of eldest household member (18-44)	45-64	0.20	3.19	—		—		-0.40	-2.16
	65-74	—		—		—		-0.34	-2.22
	75+	—		—		—		-0.34	-2.22
Household Location									
Population density (urban)	Rural	0.24	2.68	—		—		—	
Land-use diversity		—		—		—		—	
Car network density		—		—		—		—	
Walkability		-0.05	-4.66	—		—		—	
Transit accessibility		—		—		-0.35	-1.83	1.02	3.36
Census division (New England, East South Central, or Pacific)	Middle Atlantic	-0.46	-4.20	—		-0.13	-1.66	-0.46	-1.70
	East North Central	-0.14	-1.97	—		—		—	
	West North Central	—		—		—		—	
	South Atlantic	-0.24	-2.66	—		-0.12	-1.74	—	
	West South Central	0.09	1.69	0.33	1.69	-0.12	-1.69	—	
	Mountain	—		—		—		—	
Endogenous Effects									
Vehicle ownership (0-2)	3 or more vehicles	0.86	5.25	0.47	2.17	—		0.48	2.46
Thresholds									
0 1		0.79	5.18	4.08	6.38	1.23	14.27	2.63	12.13
1 2		2.42	13.92	—		2.55	19.04	2.84	12.55
2 3		3.12	19.38	—		2.97	26.46	—	
3 4		—		—		—		—	
4 5		—		—		—		—	
Correlations									
Number of Vehicles		0.21	1.97	—		0.25	3.57	—	
Gasoline SUV		-0.17	-2.09	—		-0.16	-2.48	—	
Gasoline Pickup		—		—		—		—	
Gasoline Compact		—		—		—		—	
Gasoline Minivan		—		—		0.10	1.72	—	

TABLE 3 (Continued)

Explanatory Variables (base category)		Gasoline Minivan		Electric Minivan		Gasoline Sports Car		Electric Sports Car	
		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Latent Constructs									
Green Lifestyle Propensity		—		1.09	2.59	—		—	
Safety Consciousness		—		—		—		—	
Vehicle Status Perception		-0.12	-1.70	-0.59	-1.86	0.21	2.46	0.32	1.91
Demographics									
Household income (less than \$25,000)	\$25,000 - \$49,999	—		—		—		—	
	\$50,000 - \$99,999	—		—		—		0.41	1.69
	\$100,000 - \$149,999	—		—		—		0.39	1.72
	\$150,000 - \$199,999	—		0.34	1.82	—		0.39	1.72
	\$200,000 or more	0.18	1.75	0.55	1.71	0.35	2.24	0.73	2.01
Educational attainment (less than high school)	High school diploma	—		—		—		—	
	Undergraduate degree	-0.13	-1.74	—		—		—	
	Graduate degree	-0.17	-1.79	—		—		0.38	1.74
Race (White)	Non-white	—		—		0.13	1.84	—	
Ethnicity (not Hispanic)	Hispanic	—		—		—		—	
Home type (single-family)	Apartment	-0.21	-1.69	—		-0.21	-1.74	—	
Tenure type (own)	Rent	—		-0.67	-1.72	-0.14	-1.81	-0.27	-1.79
Household composition (couple)	Single male adult	-0.41	-2.01	—		—		0.39	1.93
	Single female adult	-0.31	-1.77	—		-0.25	-1.97	—	
	Single parent	—		—		—		—	
	Roommate household	—		—		—		—	
	Extended family	—		—		—		—	
Presence of children (no)	Yes	0.23	2.59	0.16	1.66	-0.19	-2.25	—	
Presence of retired adults (no)	Yes	—		—		—		—	
Number of employed adults		—		0.22	1.71	0.12	3.20	0.18	1.87
Age of eldest household member (18-44)	45-64	0.10	1.68	—		-0.43	-4.83	-0.50	-2.13
	65-74	0.16	1.84	—		-0.43	-4.83	-0.86	-1.94
	75+	0.29	2.09	—		-0.39	-2.74	-0.86	-1.94
Household Location									
Population density (urban)	Rural	—		—		—		—	
Land-use diversity		—		—		—		—	
Car network density		—		—		—		—	
Walkability		—		—		—		—	
Transit accessibility		—		—		—		0.59	1.69
Census division (New England, East South Central, or Pacific)	Middle Atlantic	—		—		—		-0.44	-1.97
	East North Central	0.19	1.81	—		—		—	
	West North Central	—		—		—		—	
	South Atlantic	—		—		—		—	
	West South Central	—		—		—		—	
	Mountain	—		—		—		—	
Endogenous Effects									
Vehicle ownership (0-2)	3 or more vehicles	—		0.65	1.91	0.42	3.72	0.27	1.67
Thresholds									
0 1		1.69	15.05	4.55	4.77	1.48	12.53	2.90	5.65
1 2		3.01	15.36	—		2.66	15.71	—	
2 3		—		—		2.84	16.10	—	
3 4		—		—		—		—	
4 5		—		—		—		—	
Correlations									
Number of Vehicles		0.29	3.45	—		0.31	3.37	—	
Gasoline SUV		—		—		—		—	
Gasoline Pickup		—		—		—		—	
Gasoline Compact		—		—		—		—	
Gasoline Minivan		—		—		—		0.12	1.83

4.3. Model Fit

Model fit measures are presented in the upper portion of Table 4. The proposed joint model is compared with an independent model specification in which each behavioral outcome is estimated separately. As such, the independent model does not account for correlations among the behavioral outcomes and is unable to capture the joint nature of the behavioral response process. In addition, the independent model ignores the fact that some outcome combinations are infeasible.

A review of the model fit statistics clearly indicates that the proposed model provides a superior representation of the observed data. The predictive log-likelihood at convergence improves from -25,260.53 for the independent model to -25,082.31 for the proposed model. Although the proposed model estimates a larger number of parameters (253 versus 231), it nevertheless yields a lower Bayesian Information Criterion (25,575.11 versus 25,710.47), indicating that the improvement in model fit more than offsets the increase in model complexity. Likewise, the adjusted likelihood ratio index increases from 0.075 to 0.080, while the average probability of a correct prediction improves from 0.118 to 0.124. Finally, the likelihood ratio statistic of 356.44 is much larger than the critical chi-square value with 22 degrees of freedom at any reasonable level of significance, confirming that the proposed specification offers a statistically significant improvement in fit over the independent model. Overall, all model fit measures consistently favor the proposed joint model, demonstrating the value of explicitly accounting for correlations among the behavioral outcomes.

5. AVERAGE TREATMENT EFFECTS

The effects of the exogenous variables and latent constructs on the main outcomes presented in Table 3 refer to the effects on the underlying propensities for each of the outcomes. As such, they do not provide the true magnitude of, or even the direction of, the effects of each of the exogenous variables on the probabilities of choosing each outcome.

The average treatment effect (ATE) is used to translate these propensity effects into easily interpretable exogenous variable effects. The logic of the calculation can be illustrated using household income as an example. The income of all households in the dataset is first set to the base level of “Less than \$25,000,” and the multivariate probability predictions of selecting each combination of outcomes are calculated for every household in the sample. Marginalizing across this full set of predicted outcome combinations then yields, for each household, the probability of selecting each ordinal level of each individual outcome dimension. For the “number of vehicles” dimension, the expected number of vehicles owned by each household is calculated by multiplying these probabilities by the number of vehicles corresponding to each ordinal level (a value of “5” is assigned to the highest ordinal level, “5 or more vehicles”). Averaging these expected values across all households in the sample yields the average vehicle ownership level under the baseline income scenario. For each body-type/fuel-type combination, we focus instead on the share of households owning one or more vehicles of that type, computed as the average (across all households) of the probabilities summed across the relevant ordinal levels for that outcome.

This entire procedure is then repeated with household income set uniformly to the treatment level (“\$200,000 or more” in this example), while holding every other variable in the model at its observed value. Comparing the resulting average vehicle ownership level and body-type/fuel-type ownership shares under the treatment scenario to their counterparts under the baseline scenario isolates the effect attributable to household income alone. The percent change between these baseline and treatment values is reported for each exogenous variable and latent construct (for the latent constructs, we leave all estimated latent construct values at their estimated level for the base

case, and increase each by 1 unit for the treatment case; since the latent constructs are unitless, a “1 unit increase” refers to a change normalized to the scale of the error components, which is fixed to 1 for identification purposes) in the lower section of Table 4. This percent change – rather than the raw propensity effects in Table 3 – represents the magnitude of a variable's overall influence on vehicle holdings and type choice (for exogenous variables, these ATEs account for the combination of direct effects and indirect effects through the latent constructs).

For example, the value of 48.8 in the row labeled “household income” and first numeric column of the lower section of Table 4 indicates that households with an income of “\$200,000 or more” own 48.8% more vehicles on average than households with incomes of “Less than \$25,000.” Similarly, the value of 52.8 in the next column may be interpreted as indicating that households with an income of “\$200,000 or more” are 52.8% more likely to own at least one gasoline SUV compared with households with incomes of “Less than \$25,000.” The same interpretation applies to every other cell in the lower section of Table 4. Each value expresses, for the corresponding exogenous variable or latent construct, the percent change in average vehicle ownership or vehicle-type ownership share associated with moving from the base level to the treatment level shown in the second and third columns of the table.

TABLE 4 Model Fit and Average Treatment Effects (ATEs)

Disaggregate Fit Metric				Proposed Model						Independent Model					
Predictive Log-Likelihood at Convergence				-25082.31						-25260.53					
Predictive Log-Likelihood at Constants				-27543.83						-27543.83					
Number of Parameters				253						231					
Adjusted Likelihood Ratio Index				0.080						0.075					
Bayesian Information Criterion				25575.11						25710.47					
Average Probability of a Correct Prediction				0.124						0.118					
Likelihood Ratio Test				$356.44 > \chi^2_{(22,0.0001)} = 55.52$											
Treatment Variable	Base	Treatment	Vehicle Ownership	Gasoline SUV	Electric SUV	Gasoline Sedan	Electric Sedan	Gasoline Pickup	Electric Pickup	Gasoline Compact	Electric Compact	Gasoline Minivan	Electric Minivan	Gasoline Sports Car	Electric Sports Car
Latent Constructs															
Green Lifestyle Propensity	Current values	1 unit increase	-7.4	-16.9	57.3	4.4	34.6	-9.3	97.4	-11.6	34.1	-17.8	523.5	-17.7	-29.7
Safety Consciousness	Current values	1 unit increase	2.8	8.1	7.0	1.5	8.6	-5.9	10.2	-15.2	-33.4	6.7	10.3	5.9	10.0
Vehicle Status Perception	Current values	1 unit increase	-2.0	2.7	8.3	-14.5	10.8	-8.2	15.5	6.0	12.0	-14.4	-72.5	55.5	127.3
Household Demographics and Location															
Household income	< \$25,000	≥ \$200,000	48.8	52.8	488.5	5.2	327.7	14.8	743.6	26.9	342.6	103.9	416.9	171.9	849.3
Education	< high school	Grad. degree	7.5	-1.0	100.4	22.4	268.2	-26.3	67.6	8.3	32.2	-14.5	230.3	10.4	196.8
Race	White	Non-White	-5.5	-13.3	21.7	11.6	13.1	-19.2	37.2	-16.2	8.3	-2.2	202.0	14.9	-23.5
Ethnicity	Not Hispanic	Hispanic	3.5	-3.1	9.4	1.9	5.7	20.0	15.5	14.4	6.3	-1.4	88.7	-5.7	-11.7
Home type	Single-family	Apartment	-14.0	-12.6	-29.4	2.0	4.7	-35.3	18.0	-3.8	5.4	-37.4	115.3	-43.4	-21.0
Tenure type	Own	Rent	-7.5	-2.9	-52.2	11.3	-68.9	-27.6	-14.5	-8.6	-65.2	-13.9	-82.8	-31.2	-55.7
Household composition	Multi-adult	Single adult	-27.7	-27.7	-34.4	-12.3	-43.8	-42.5	61.0	-6.3	-17.1	-59.3	-22.8	-27.8	46.8
	Single male	Single female	-5.6	19.5	-46.8	4.2	-68.4	-56.5	-68.2	-0.5	4.3	30.0	32.8	-49.3	-86.4
# children	None	One or more	-3.5	-2.5	48.1	-7.7	67.8	-4.1	650.0	-17.5	62.3	57.3	146.1	-31.6	-3.6
# retired adults	None	One or more	6.7	7.8	-4.3	-1.6	-2.5	18.8	-7.6	11.8	-2.8	-0.9	-42.1	3.9	8.7
# employed adults	None	One or more	14.0	9.1	25.4	7.3	8.5	25.4	10.1	20.1	10.0	8.1	89.4	35.8	72.1
Age of eldest household member	18-44 years	75+ years	1.4	2.3	-63.7	12.8	-50.6	2.6	-9.1	-1.4	-60.8	81.1	-52.7	-56.7	-104.8
Population density	Urban	Rural	-1.7	-7.2	9.0	-14.9	10.8	36.0	14.4	5.5	13.2	9.4	13.0	7.9	13.1
Land-use diversity	Current values	20% increase	1.1	0.5	2.7	0.7	3.1	1.2	4.0	1.5	3.7	2.5	3.9	2.3	3.8
Car network density	Current values	20% increase	0.1	-0.1	-0.6	0.5	2.3	-0.1	-0.7	-0.2	-1.0	-0.3	-0.8	-0.3	-0.7
Walkability	Current values	20% increase	-2.8	-4.1	12.1	0.3	13.2	-10.9	1.4	0.8	0.8	1.3	1.1	1.0	1.2
Transit accessibility	Current values	20% increase	-0.3	-0.1	-0.8	-0.7	-0.8	-0.1	-0.5	-0.8	11.6	-0.2	-0.7	-0.3	4.1
Endogenous Effects															
Vehicle Ownership	0-2	3 or more	--	-7.3	-3.4	-8.2	19.6	145.3	106.8	-17.0	88.8	-26.0	167.6	61.9	16.8

6. DISCUSSION AND CONCLUSIONS

This study presents a multivariate ordered probit model that jointly estimates the total number of vehicles a household owns alongside the number of vehicles held in each of 12 body-type/fuel-type combinations, using data from Wave 1 of the Transportation Heartbeat of America Survey. Unlike the multiple discrete-continuous extreme value framework commonly used in prior vehicle composition modeling work, which identifies only whether a household holds at least one vehicle of a given type, this model recovers actual vehicle counts by type while allowing overall fleet size to shape vehicle type-specific preferences. Three stochastic latent constructs (green lifestyle propensity, safety consciousness, and vehicle status perception) capture the attitudes and lifestyle orientations that mediate much of the relationships between household demographics and vehicle preferences. Model fit statistics confirm the value of this joint multivariate modeling approach, with the proposed specification outperforming an independent model on every measure considered, demonstrating that the correlations linking fleet size to vehicle-type composition are both statistically meaningful and behaviorally consequential.

Attitudes and lifestyle preferences prove to be a distinct and powerful channel of influence on vehicle holdings. Green lifestyle propensity has only a modest effect on total fleet size but a considerably larger effect on composition; environmentally-oriented households steer away from gasoline SUVs in particular and toward electric vehicles across nearly every body-type. This is not a surprising result on its face, but its magnitude matters. It shows that environmental attitudes reshape fleet composition even when they leave overall vehicle ownership largely unchanged. This reinforces the value of continuing to promote policies that cultivate sustainable lifestyles, including environmental education and financial incentives that help households translate stated environmental values into realized changes in vehicle-type choice.

Safety consciousness pulls in the opposite direction, drawing households toward larger vehicles, especially gasoline SUVs, and away from compact cars. This preference carries a notable social cost. As other researchers have observed, larger vehicles impose greater negative externalities and heightened safety risks on other road users, even as they make their own occupants feel safer (see, for example Toy and Hammitt, 2003; Edwards and Leonard, 2022). This suggests that safety-oriented policy may be better served by promoting vehicle-level safety technologies (such as automatic emergency braking, collision avoidance systems, and back-up cameras) that can deliver genuine safety gains without reinforcing a shift toward ever-larger vehicles. Vehicle status perception, meanwhile, has little bearing on overall fleet size but shapes composition sharply. Households that view vehicles as status symbols gravitate toward sports cars (both gasoline and electric), while functionally-oriented households favor sedans, pickup trucks, and minivans. Together, these three attitudinal dimensions demonstrate that attitudes and lifestyle preferences matter when it comes to vehicle preferences, thus constituting independent lever that policy can act on directly.

Socio-demographic characteristics remain powerful determinants in their own right, with significant differences in EV preferences emerging across income, education, age, home type, and household composition. Income stands out as the most critical of these. Households earning \$200,000 or more are more than 300% more likely to adopt electric vehicles across every body-type than households earning less than \$25,000, underscoring the importance of affordability even in the wake of growing attitudinal support for sustainability. Renters show markedly reduced EV ownership, consistent with their limited control over installing home charging infrastructure, while apartment dwellers show reduced interest in SUVs, minivans, and sports cars, plausibly reflecting the practical challenges of parking larger vehicles in denser settings. This suggests that

electrification policy cannot rely on attitudinal shifts or income growth alone; addressing structural barriers such as charging access is equally essential to converting positive environmental attitudes into actual vehicle-type choices.

Built-environment characteristics contribute a further, complementary layer of findings. Improving walkability and transit accessibility is associated with a small but statistically significant reduction in overall vehicle holdings, and transit accessibility in particular is also associated with a distinct shift toward electric vehicle ownership at the level of specific vehicle types – suggesting that transit and walking friendly environments and EV adoption may be mutually reinforcing rather than competing strategies for reducing conventional automobile dependence.

A further consequential finding concerns the endogenous relationship between total fleet size and vehicle-type composition. Electric vehicles of nearly every body-type are considerably more common among households with three or more vehicles than among households with smaller fleets, indicating that EVs are still, for the most part, being adopted as an additional vehicle within an already-diversified fleet rather than as a household's sole vehicle. Gasoline pickup trucks and sports cars follow a similar pattern. This carries a direct policy implication, suggesting that EV incentive programs and outreach may achieve greater near-term impact by targeting multi-vehicle households, for whom an EV can be added without displacing existing flexibility. On the other hand, single-vehicle households may view an EV purchase with greater levels of skepticism.

Collectively, these findings offer practical value for transportation planners and policymakers seeking to understand how household attitudes, lifestyle preferences, and demographics jointly shape vehicle ownership and fleet composition. Because the model jointly estimates total holdings alongside type-specific choices, it supports more realistic fleet forecasts than approaches that treat these decisions independently – helping to better inform infrastructure planning, parking demand, charging deployment, energy consumption, and emissions strategy. The framework can be used for the evaluation of electrification policy while recognizing that households manage an entire vehicle “portfolio” rather than replacing vehicles in isolation, and can be used to examine how demographic shifts, land-use patterns, and changing attitudes will shape future fleet composition.

Some limitations point to natural directions for future research. The analysis relies on a single cross-sectional wave of data, capturing a snapshot rather than the dynamic process of vehicle acquisition and disposal over time. Future waves of the survey could support longitudinal modeling of vehicle transactions. The model also omits vehicle price, operating cost, and local model availability, all of which plausibly interact with the attitudinal and demographic factors examined in the study. Incorporating these supply-side considerations represents a natural next step for future work.

AI STATEMENT

Artificial intelligence tools – ChatGPT and Claude – were used to support the preparation of this manuscript, assisting with formatting content and refining language. All AI-assisted output was critically reviewed, revised, and validated by the authors. The study design, analysis, interpretation of results, and conclusions reflect the authors’ academic and professional judgment. AI tools improved efficiency and communication but did not substitute for engineering judgment, technical review, or responsibility for the final content. The authors are solely responsible for all content, including any errors or omissions.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: D. Robbennolt, I. Batur, R.M. Pendyala, C.R. Bhat; data collection: D. Robbennolt, I. Batur, R.M. Pendyala, C.R. Bhat; analysis and interpretation of results: C. Starks, D. Robbennolt, H. Hwang, I. Batur, R.M. Pendyala, C.R. Bhat; draft manuscript preparation: C. Starks, D. Robbennolt, I. Batur, R.M. Pendyala, C.R. Bhat. All authors reviewed the results and approved the final version of the manuscript.

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