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Does Ridehailing Use Affect Vehicle Ownership or Vice Versa? An Exploratory Investigation of the Relationship Using a Latent Market Segmentation Approach

Irfan Batur[1], Abbie C. Dirks[1], Aupal Mondal[2], Chandra R. Bhat[2,3], and Ram M. Pendyala[1]

Abstract
This paper presents an examination of the interrelationship between household vehicle ownership and ridehailing use frequency. Both variables constitute important mobility choices with significant implications for the future of transport. Although it is generally known that these two behavioral phenomena are inversely related to one another, the direction of causality is rather ambiguous. Do vehicle ownership levels affect ridehailing use frequency, or does the adoption and use of ridehailing services affect vehicle ownership? If ridehailing services affect vehicle ownership, then it is plausible that a future of mobility-as-a-service would be characterized by lower levels of vehicle ownership. To explore the degree to which these causal relationships are prevalent in the population, a joint latent segmentation model system was formulated and estimated on a survey data set collected in four automobile-oriented metropolitan areas of the United States. The latent segmentation model system recognized that the causal structures driving the mobility choices of individuals were not directly observable. Model estimation results showed that 58% of the survey sample followed the causal structure in which ridehailing use frequency affected vehicle ownership. This finding suggests that there is considerable structural heterogeneity in the population with respect to causal structures and that ridehailing use does indeed hold considerable promise to effect changes in private vehicle ownership in the future.

Keywords
planning and analysis, transportation demand forecasting, demand estimation, general

One of the most notable and impactful mobility innovations of the past decade has been ridehailing services, which allow individuals to summon and pay for a ride in real-time using the convenience of a mobile app. Such vehicles are generally owned, operated, and maintained by individual drivers, who are similar to freelance workers, setting their own working hours and operating as independent contractors. Individuals, acting as drivers, can then provide rides to any individual who signs up to use the ridehailing service platform. Examples of ridehailing services include Lyft in the United States, Uber in many countries, Didi in China, and Ola in India. These services are sometimes called mobility-on-demand services or mobility-as-a-service (MaaS). Despite subtle distinctions between these terms, they will be used interchangeably within the context of this paper.

Ridehailing services have become very popular in many cities around the world, with Uber arguably the world's largest ridehailing service provider. Although official statistics are hard to come by, informal sources

[1]School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ
[2]Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, Austin, TX
[3]The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

Corresponding Author:
Ram M. Pendyala, ram.pendyala@asu.edu

(*1*) report that Uber has nearly 100 million active users and completes 1.44 billion rides every quarter. Major ridesharing platforms in other countries report similarly impressive numbers. Even though the mode share of ridehailing services remains modest, especially in the United States, it is fair to say that ridehailing is a well-established and entrenched mode of transportation in most metropolitan areas. Ridehailing services have grown to such an extent that decreases in transit ridership and increases in urban congestion are being attributed, at least in part, to the rise of ridehailing services (*2*, *3*).

Because of the widespread adoption of ridehailing services as a mode of transportation, transportation demand forecasting models need to be enhanced to reflect ridehailing service usage patterns and their impacts on other modes of transportation. In addition, metropolitan areas and planning agencies have been grappling with implementing policies and strategies to ameliorate any adverse impacts of ridehailing services in their jurisdictions. Owing to these myriad and complex planning considerations and modeling needs, a vast body of literature exploring and documenting the adoption and impacts of ridehailing services has emerged (*4*). Several studies have examined various facets of ridehailing adoption, including an exploration of market segments more and less likely to use such services, the travel characteristics of trips undertaken by ridehailing services, and the extent to which ridehailing services may be contributing to vehicle miles traveled resulting from deadhead miles and zero-occupant travel (*5–8*).

Among the many aspects of interest is the interrelationship between ridehailing service usage and vehicle ownership. Multiple strands of research have explored this intricate relationship. Several studies have modeled ridehailing usage as a function of socioeconomic and demographic attributes, built environment attributes, and vehicle availability. These studies have consistently documented an inverse relationship between ridehailing usage and vehicle ownership, with individuals in households of higher vehicle ownership exhibiting lower levels of ridehailing usage (*6*, *9*, *10*). This is behaviorally intuitive: increased access to a personal vehicle would decrease the need to use ridehailing services. Individuals in such households likely use such services only under special circumstances (e.g., trips to/from the airport, when a personal vehicle breaks down).

Another strand of research has focused on the vehicle ownership implications of ridehailing services. With the widespread availability of ridehailing services, it is potentially feasible for households to downsize the number of vehicles they own. In other words, with time, households may shed vehicles and not replace them because of their use of ridehailing services. Several studies have focused on the potential for ridehailing services to contribute to lower levels of private vehicle ownership in the future (*8*, *11*). Indeed, some studies report that individuals who have embraced ridehailing services as a mobility option have reduced the number of vehicles they own or are contemplating such a reduction in the future (*12*, *13*).

Past research suggests a probable two-way interaction between ridehailing usage and vehicle ownership. On the one hand, vehicle ownership levels may dictate the extent of ridehailing service usage, and on the other hand, the extent of ridehailing service adoption may have an impact on vehicle ownership. These two causal directions are likely to coexist in the population, and it would be useful to determine the extent to which each causal structure is prevalent in a population. Virtually all transportation demand forecasting models in practice assume that ridehailing usage is influenced by vehicle ownership, without considering the possibility that the other direction may also hold true. If both causal directions are prevalent to a significant degree, then transportation demand forecasting models should reflect this duality accurately.

This study adopted a novel latent segmentation modeling approach to decipher the extent to which the two causal directions are prevalent in the population. Survey data collected in 2019 in four automobile-oriented metropolitan areas of the United States were used. The survey has detailed information about individual ridehailing usage and vehicle ownership patterns, in addition to a host of socioeconomic and demographic attributes. A latent segmentation approach was adopted because the causal relationship between ridehailing use and vehicle ownership was not observed for each observation in the data set—the causal relationship was unobserved and therefore treated as *latent*. Each observation may belong to one or the other of the causal structures, but which one is not observable. Therefore, based on a mixing approach, we estimated the probability of each observation belonging to each segment, thus providing the ability to calculate the size of each causal market segment. In addition, were it possible to derive the profiles of each latent market segment, this would provide valuable insights into their characteristics. Armed with such knowledge, it would be possible to enhance transportation demand forecasting models so that they reflected the appropriate causal structure for different subgroups in the population. It is recognized that vehicle transactions (turnover) occur over long periods of time. However, as ridehailing services have been in vogue for more than a dozen years now, enough time has elapsed for ridehailing services to potentially affect household vehicle ownership levels. It was therefore anticipated that the latent segmentation approach employed in this study would be able to uncover the two causal structures in the population using the 2019 survey data set.

The remainder of this paper is organized as follows. The next section presents a description of the data set used in this study. The third section presents the modeling framework and methodology. The fourth section presents model estimation results, and the fifth offers a discussion and concluding remarks.

Data Description

The data used in this study were derived from a survey conducted in 2019 in four automobile-oriented metropolitan areas in the United States: Phoenix (AZ), Austin (TX), Atlanta (GA), and Tampa (FL). The primary objective of the survey was to gather detailed information about attitudes and perceptions toward emerging mobility services and transportation technologies, lifestyle preferences and mobility choices, and socioeconomic and demographic attributes. The survey was comprehensive in nature and provided an in-depth perspective on how individuals felt about ridehailing services and the extent to which they currently use ridehailing services. The survey was administered using various survey administration methods, with the recruitment of survey respondents undertaken through email and postal mail communications, Facebook advertisements, and news and media releases. To maximize response rates, rigorous reminder protocols were implemented, and respondents were given incentives. These efforts resulted in a total respondent sample of 3,465 individuals, with each respondent belonging to a unique household. The same survey instrument was deployed in all regions, thus enabling consistent pooling of data sets across areas. More details about the survey instrument, sampling strategies, response rates, and respondent profiles may be found elsewhere (*14*).

In accordance with the study objectives, respondents retained in the analysis sample were limited to those familiar with ridehailing services, regardless of whether they actually use the services. It is unlikely that there is any relationship between ridehailing use and vehicle ownership for those unfamiliar with ridehailing services. After removing the individuals unfamiliar with such services, and cleaning missing and obviously erroneous records, the final sample included 3,146 individuals.

Table 1 presents an overview of sample characteristics. In general, the sample exhibited the desired level of variability for conducting a modeling exercise of the nature undertaken in this study. Females comprised 57% of the sample. More than one-quarter of the sample fell into the lowest age bracket of 18 to 30 years, with individuals widely distributed across all other age groups. Nearly 94% of respondents held a driver's license. Over 64% of the sample were either full- or part-time workers and roughly one-quarter were neither workers nor students. As is commonly the case with surveys of this nature, the sample was skewed toward individuals with a higher level of education. Only 8.5% had a high school diploma or less, whereas one-quarter possessed a graduate degree. With respect to race, 71% of the sample was White, 9% were Asian or Pacific Islanders, and 7.8% were Black. A little more than one-third of the sample resided in households with an annual income between $50,000 and $99,999. The rest of the sample was distributed across other income groups, offering a good representation of all income levels. About 40% of individuals in the sample resided in larger households with three or more members, whereas 21% reported being in single-person households. There was a strong relationship between housing unit type and home ownership. Seventy percent of respondents resided in stand-alone homes and two-thirds owned their homes. With respect to vehicle ownership, 4% of the respondents lived in households with no vehicles. About 40% resided in households with two vehicles, and another 32.6% resided in households with three or more vehicles. Given the automobile-oriented nature of the survey locations, the high auto ownership level was consistent with expectations. The sample was fairly evenly split between Phoenix, Austin, and Atlanta, with a smaller percentage residing in Tampa.

Endogenous Variables and Attitudinal Indicators

The two endogenous variables of interest in this study are ridehailing use frequency and vehicle availability (which represents vehicle ownership, but in the form of a per-adult vehicle ownership level). Thus, access to household vehicles was computed as the number of vehicles per adult (18 +) for each record. This was used to define three categories of vehicle availability: none (zero vehicle), deficient (fewer vehicles than adults), and sufficient (at least as many vehicles as adults). As shown in Table 1, 3.9% reported no vehicle available, 22% resided in vehicle-deficient households, and 74.1% in vehicle-sufficient households. The frequency of ridehailing usage was captured in the survey with the following statement: "How often do you generally use private ridehailing services?" Accompanying this statement, respondents were given a definition of private ridehailing service: "an on-demand mobility service that provides door-to-door (or curb-to-curb) transportation via a smartphone app"; private mode solely involved the passenger and their own travel companions (if any). Thirty-eight percent of the respondents indicated that they never used such services. About 43% rarely used ridehailing services (i.e., less than once a month), whereas 15% reported using ridehailing services about once a month. About 4% used the services frequently (at least once a week). These statistics were all consistent with expectations and aligned with the low transit ridership levels in these markets (*4*). The study recognized that the frequency of ridehailing use may be

Table 1. Socioeconomic and Demographic Characteristics of the Sample

Individual demographics (*N* = 3,146)		Household characteristics (*N* = 3,146)	
Variable	Percentage	Variable	Percentage
Gender		Household annual income	
Female	57.1	Less than $25,000	10.2
Male	42.9	$25,000 to $49,999	14.9
Age category		$50,000 to $99,999	34.0
18–30 years	26.1	$100,000 to $149,999	21.8
31–40 years	11.9	$150,000 to $249,999	12.8
41–50 years	15.5	$250,000 or more	6.3
51–60 years	16.4	Household size	
61–70 years	16.1	One	21.2
71 + years	14.0	Two	38.5
Driver's license possession		Three or more	40.3
Yes	93.6	Housing unit type	
No	6.4	Stand-alone home	69.9
Employment status		Condo/apartment	21.1
A student (part-time or full-time)	10.0	Other	9.0
A worker (part-time or full-time)	53.6	Home ownership	
Both a worker and a student	10.7	Own	67.9
Neither a worker nor a student	25.7	Rent	26.3
Educational attainment		Other	5.8
Completed high school or less	8.5	Vehicle ownership	
Some college or technical school	28.5	Zero	3.9
Bachelor's degree(s)	37.7	One	23.7
Graduate degree(s)	25.3	Two	39.8
Race		Three or more	32.6
Asian or Pacific Islander	9.0	Location	
Black or African American	7.8	Atlanta, GA	30.1
Native American	0.4	Austin, TX	32.3
White or Caucasian	71.0	Phoenix, AZ	30.4
Other	11.8	Tampa, FL	7.2
Main outcome variables			
Ridehailing use frequency		Household vehicle availability	
Never	38.0	None	3.9
Rarely (<once per month)	42.8	Deficient (<1 per adult)	22.0
Monthly (about once per month)	15.1	Sufficient (at least 1 per adult)	74.1
Weekly (at least once per week)	4.1		

affected by the type of locale in which the respondents resided, as those residing in distant suburban locations or rural areas may not have access to ridehailing services to the same degree that individuals residing in denser urban environments might enjoy. To reflect this, the model specification included built environment attributes as explanatory variables (e.g., population density).

Figure 1 shows the bivariate relationship between the two endogenous variables. A pattern is discernible. Among individuals residing in zero-vehicle households, 18% used ridehailing services weekly, and another 23.6% used the services monthly. These percentages stand in stark contrast to those who resided in households with vehicles available. In vehicle-deficient households, 4.2% of individuals used ridehailing services frequently, suggesting that households were effective at sharing limited household vehicles. In vehicle-sufficient households, 3.4% used ridehailing services on a weekly basis. Likewise, whereas 15.6% of individuals in vehicle-deficient households used ridehailing services monthly, a slightly smaller 14.4% of individuals in vehicle-sufficient households used ridehailing services at such a frequency. Also, 36.3% of individuals in vehicle-deficient households never used ridehailing services; the corresponding percentage for individuals in vehicle-sufficient households was higher at 39.2%. Overall, the bivariate distribution showed a strong relationship between vehicle availability and ridehailing frequency. This paper further aims to shed light on the nature of the causal relationship between these two endogenous choice variables.

A key aspect of this study's methodological approach involved incorporating and explicitly accounting for attitudinal variables that capture perceptions, values, and preferences. The survey included a large battery of attitudinal statements to elicit perceptions, values, and preferences with respect to mobility options, lifestyle

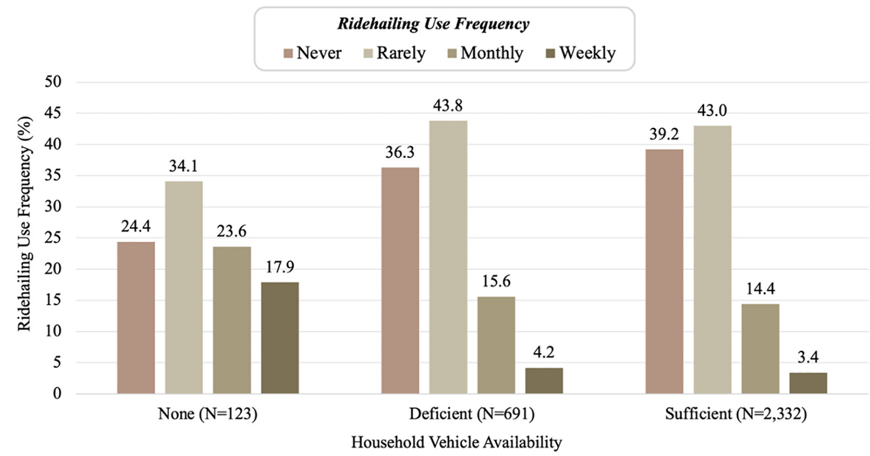

Figure 1. Household vehicle availability by ridehailing use frequency ($N = 3{,}146$).

preferences, and outlook in relation to ridehailing services. Accordingly, four latent attitudinal constructs were adopted in this study: time sensitivity, technology savviness, (positive) ridehailing service perceptions, and transit-oriented lifestyle (tendency). These latent attitudinal constructs were developed based on evidence in the literature (*6*, *15*), behavioral intuitiveness, and consideration of the types of variables that are most likely to play a role in shaping vehicle availability and ridehailing frequency choices. Each latent construct was represented by three highly correlated attitudinal indicators, thus calling for the estimation of latent factors that serve as a composite representation of disparate attitudinal dimensions. Figure 2 depicts the latent constructs and the attitudinal statements defining them. A detailed discussion is not provided here in the interest of brevity. The figure shows that the attitudinal statements were intuitively related to the constructs of interest and distributed in the sample in a manner consistent with expectations.

A standard factor analysis (principal components with varimax rotation) was conducted to develop the latent factors and compute the latent factor scores for each observation in the data set. The latent factors were then used in the model estimation exercise. Although latent attitudinal constructs are endogenous variables themselves, they were treated as exogenous explanatory variables in this study. Treating them as endogenous variables within the context of a latent segmentation modeling framework that aimed to simultaneously capture multiple causal relationships between endogenous choice variables presented an analytical and computational challenge. The number of possible permutations of the causal relationship structures became vast, thus presenting computational complexity. Accordingly, only ridehailing use and vehicle availability were treated as endogenous variables and the model structure focused on the nature of the causal relationship between them.

Modeling Framework

This section presents the modeling framework adopted. The study was concerned with unraveling the direction of the causal relationship between ridehailing frequency and vehicle availability (both comprise frequencies or counts with a natural ordered representation). Estimation of bidirectional causal models is only feasible when both behavioral choice variables are continuous; under that restrictive scenario, a mutually reinforcing relationship between two dependent variables may be explicitly estimated. However, when the choice variables are discrete or limited dependent in nature (i.e., not continuous), which is often the case in travel behavior research, then a bidirectional relationship is not identified, and identification restrictions must be imposed for logical consistency and estimability (*16*). This necessitates the estimation of recursive simultaneous equation models, in which a specific direction of causality is assumed for all observations. However, all individuals in a population are unlikely to follow the same single causal structure; this study was therefore motivated by the desire to identify the extent to which multiple causal relationships coexisted in the study sample and to understand the differences in socioeconomic and demographic characteristics between market segments defined by the two causal structures. Such insights would help inform demand forecasting models, enabling them to better represent structural heterogeneity (in causal relationships between mobility choice variables) in the population. They would also guide policies and the design of behavioral change interventions.

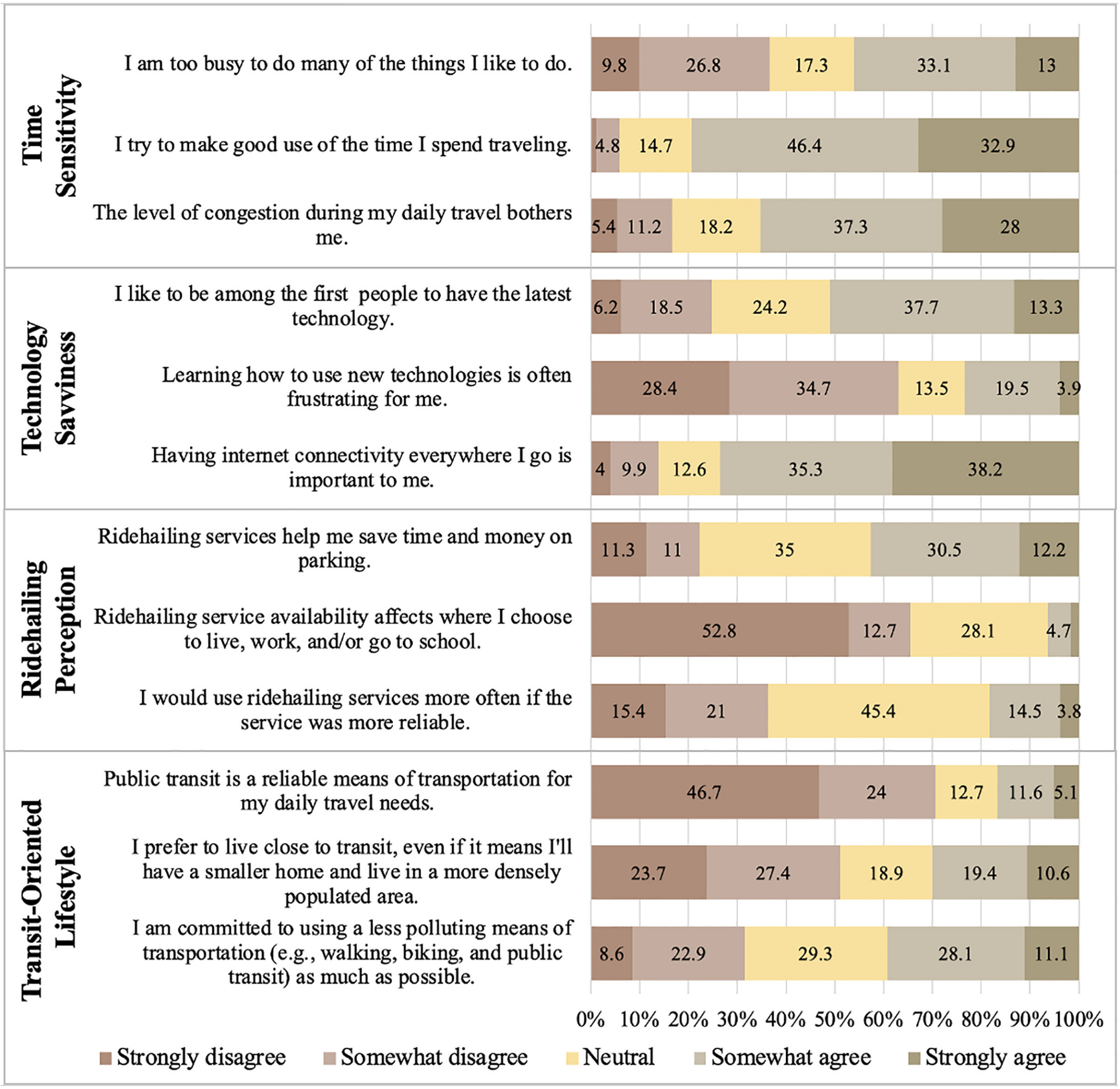

Figure 2. Agreement with attitudinal indicators defining latent constructs ($N = 3{,}146$).

It must be recognized that cause-and-effect patterns, in general, unfold over time, involve leads and lags, and are inherently dynamic in nature. Therefore longitudinal panel data are needed to elucidate and identify causal relationships. Although such data have been collected occasionally in the profession, the prevailing norm continues to be the collection of (repeated) cross-sectional data from a sample of the population. It is nearly impossible to unravel cause-and-effect relationships that occur over time in the absence of true longitudinal panel data. Therefore, the travel behavior field has had to infer causal relationships based on cross-sectional survey data (this is the norm in the vast body of transportation modeling literature). Because cross-sectional data were used in this study, the analysis should be interpreted as invoking the notion of contemporaneous causation (*17*), which is generally defined as the concept that behavior is caused at the moment of its occurrence by all influences that are present to the individual at that moment (*18*). The authors fully recognize that vehicle transaction decisions play out over time. Therefore, a strong underlying assumption of this study is that causal relationships involving vehicle availability can be modeled within the psychological construct of contemporaneous causation. Future research needs to relax this assumption and employ longitudinal survey data to address the limitations of the cross-sectional treatment of this causal relationship.

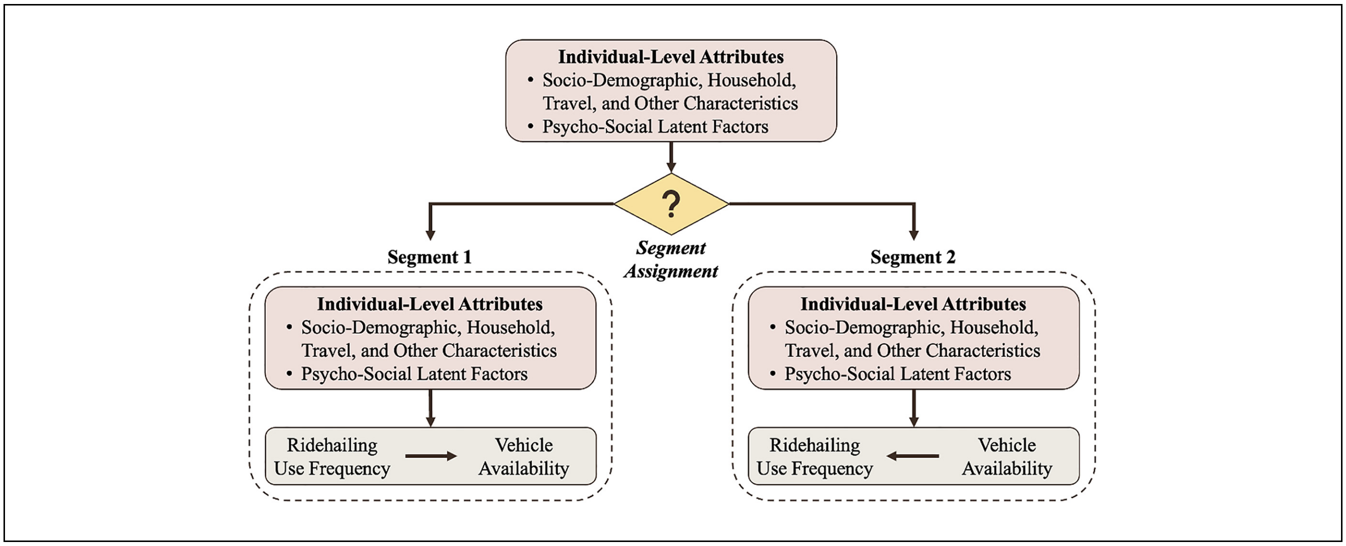

Figure 3. Latent segmentation model framework.

Model Structure

The model structure adopted in this study posits that each individual in the study sample follows one of two causal structures representing the relationship between ridehailing frequency and vehicle availability. The actual causal structure that drives the behaviors of each individual, however, was not observed explicitly. Therefore, a latent segmentation modeling approach was adopted; the approach facilitated the identification of two latent classes and the probabilistic allocation of each individual to one of the two latent market segments. This approach recognizes the interrelationship between the two choice variables. Vehicle availability could have an impact on the need for and usage frequency of ridehailing services, and conversely, the frequency of ridehailing use could affect the need to own (or dispose of) household vehicles.

The model system comprised multiple elements. A latent segmentation model component was used to assign individuals to one of the two causal segments based on their individual and household-level attributes. Then, within these segments, both variables of interest were jointly modeled as a function of an array of explanatory variables. It is important to note that the selection of exogenous variables for inclusion in the model specification and the impacts of the exogenous variables on the endogenous variables of interest may not have been the same across segments; in fact, differences in the effects and significance of exogenous variables were expected since both segments were defined by fundamentally different causal structures. Some variables were excluded from the model of a specific segment owing to their not being statistically significant or theoretically and behaviorally sound. Figure 3 offers a simplified representation of the model framework.

The Joint Model of Behavioral Choices

Consider an individual q ($q = 1, 2, 3, \ldots, Q$) facing a multi-dimensional ordered choice system. Let c be the index for the ordinal outcome ($c = 1, 2, \ldots, C; C = 2$ in our case). For ease of presentation, subscript q is dropped for the individual. Assume that the individual belongs to a specific segment, h. Define a latent propensity, y^*_{ch}, underlying the count variable, y_c, for outcome c and for segment h. Then,

$$y^*_{ch} = \boldsymbol{\beta}'_{ch}\mathbf{x} + \varepsilon_{ch},\ y_c = k_c \text{ if } \boldsymbol{\psi}_{ch,k_c-1} < y^*_{ch} < \boldsymbol{\psi}_{ch,k_c} \quad (1)$$

where $\mathbf{x}$ is an $(L \times 1)$ vector of exogenous attributes (not including a constant) as well as possibly the observed values of other endogenous variables; $\boldsymbol{\beta}_{ch}$ is a corresponding $(L \times 1)$ vector of channel-specific coefficients to be estimated (note that by restricting specific elements of $\boldsymbol{\beta}_{ch}$ to be zeros, it is possible to control which variables to estimate specific to the segment, h; furthermore, $\boldsymbol{\beta}_{ch}$ can be zero on the endogenous variables within each segment); and ε_{ch} is a random error term assumed to be standardly normally distributed; k_c represents a specific value of y_c, which can range from the value of 0 to a maximum of K_c in the sample ($y_c \in \{0, 1, 2, ..., K_c\}$). The latent count propensity, y^*_{ch}, is mapped to the observed count variable y_c by the thresholds $\boldsymbol{\psi}_{ch,k_c}$, which should satisfy the ordering conditions ($\boldsymbol{\psi}_{ch,-1} = -\infty$; $-\infty < \boldsymbol{\psi}_{ch,0} < \boldsymbol{\psi}_{ch,1} < \ldots \boldsymbol{\psi}_{ch,K_c-1} < \infty$) in the usual ordered-response fashion.

Next, vertically stack the C latent variables, y^*_{ch}, into a $(C \times 1)$ vector $\mathbf{y}^*_h$, and the C error terms ε_{ch} into another $(C \times 1)$ vector, $\boldsymbol{\varepsilon}_h$. Let $\boldsymbol{\varepsilon}_h \sim MVN_C(\mathbf{0}_C, \Xi_h)$, where $MVN_C(\mathbf{0}_C, \Xi_h)$ represents the C dimensional multivariate normal distribution with mean vector $\mathbf{0}_C$ (a $(C \times 1)$

vector of zeros) and a correlation matrix of Ξ_h specific to segment h. The off-diagonal terms of Ξ_h captures the error covariance across the underlying latent continuous propensities of the different ordered outcomes. For future use, also define the vector of thresholds for each outcome c as $\tilde{\boldsymbol{\psi}}_{ch} = (\psi_{ch,0}, \psi_{ch,1}, ...\psi_{ch,K_c-1})'$, and further vertically stack all the $\tilde{\boldsymbol{\psi}}_{ch}$ vectors into a single $\tilde{\boldsymbol{\psi}}_h$ vector.

Let an individual under consideration be observed to have the count values of k_c (c = 1,2,…C). Accordingly, stack the lower thresholds, ψ_{ch,k_c-1} ($c = 1, 2, ...C$), corresponding to the observed ordered values of the individual into a ($C \times 1$) vector $\psi_{low,h}$, and the upper thresholds, ψ_{ch,k_c} ($c = 1, 2, ...C$), into another ($C \times 1$) vector $\boldsymbol{\psi}_{high,h}$. Also, define $\boldsymbol{\beta}_h = (\boldsymbol{\beta}_{1h}, \boldsymbol{\beta}_{2h}, ..., \boldsymbol{\beta}_{Ch})'$ [$(C \times L)$ matrix]. With these notational preliminaries, the latent propensities underlying the multivariate ordered outcomes may be written in matrix form as

$$\mathbf{y}^*_h = \boldsymbol{\beta}'_h\mathbf{x} + \boldsymbol{\varepsilon}_h, \boldsymbol{\psi}_{low,h} < \mathbf{y}^*_h < \boldsymbol{\psi}_{high,h}, \\ \text{where } \mathbf{y}^*_h \sim MVN_C(\boldsymbol{\beta}'_h\mathbf{x}, \Xi_h) \tag{2}$$

Let $\boldsymbol{\delta}_h$ be the collection of parameters to be estimated for segment h, $\boldsymbol{\delta}_h = \left([\text{Vech}(\boldsymbol{\beta}_h)]', \tilde{\boldsymbol{\psi}}'_h, [\text{Vechup}(\Xi_h)]'\right)'$, where the operator "Vech(.)" row-vectorizes all the non-zero elements of the matrix/vector on which it operates, and the operator Vechup(.) row-vectorizes the upper diagonal elements of a matrix. Then the likelihood function of a single individual q may be written as

$$L(\boldsymbol{\delta}_h) = \Pr\left[\boldsymbol{\psi}_{low,h} < \mathbf{y}^*_h < \boldsymbol{\psi}_{high,h}\right] \tag{3}$$

$$= \int_{D_r} f_C(\boldsymbol{r}|\boldsymbol{\beta}'_h\mathbf{x}, \Xi_h)dr \tag{4}$$

where the integration domain, $D_r = \{\boldsymbol{r} : \boldsymbol{\psi}_{low,h} < \boldsymbol{r} < \boldsymbol{\psi}_{high,h}\}$, is simply the multivariate region of the $\mathbf{y}^*_h$ vector determined by the upper and lower thresholds. $f_C(\boldsymbol{r}|\boldsymbol{\beta}'_h\mathbf{x}, \Xi_h)$ is the multivariate normal density function of dimension C with a mean of $\boldsymbol{\beta}'_h\mathbf{x}$ and a correlation matrix Ξ_h. Bhat's matrix-based approximation method for evaluating the multivariate normal cumulative distribution function was employed to evaluate this integral, which provides an efficient and tractable formulation to approximate it (*19*).

Latent Segmentation Model

The derivation thus far is based on the notion that individual q belongs to a single segment, h. Although the actual assignment of individual q to a specific segment is not observed, it is possible to attribute a probability, π_{qh} ($h = 1, 2, \ldots, H$), to individual q belonging to segment h. The conditions that $0 \leq \pi_{qh} \leq 1$ and $\sum_{h=1}^{H} \pi_{qh} = 1$ must be met. To enforce these restrictions, following Bhat, the following logit link function is used (*20*):

$$\pi_{qh} = \frac{exp(\boldsymbol{\mu}'_h\boldsymbol{w}_q)}{\sum_{j=1}^{H} exp(\boldsymbol{\mu}'_j\boldsymbol{w}_j)} \tag{5}$$

where
$\boldsymbol{w}_q$ is a ($J \times 1$) vector of individual exogenous variables,
$\boldsymbol{\mu}_h$ is the corresponding ($J \times 1$) vector of parameters, and
$\boldsymbol{\mu}_1 = \mathbf{0}$ serves as a vector identification condition.
Defining $\boldsymbol{\delta} = [\boldsymbol{\delta}'_1, ..., \boldsymbol{\delta}'_h; \boldsymbol{\mu}'_1, ..., \boldsymbol{\mu}'_h]'$, then the likelihood function for individual q is

$$L_q(\boldsymbol{\delta}) = \sum_{h=1}^{H} \pi_{qh}[L(\boldsymbol{\delta}_h)|q \in \text{segment } h)] \tag{6}$$

and the overall likelihood function is then given as

$$L(\boldsymbol{\delta}) = \prod_q L_q(\boldsymbol{\delta}) \tag{7}$$

Model Estimation Results

This section summarizes the model estimation results. Before estimating the joint model system, a separate confirmatory factor analysis (CFA) was conducted to construct the latent attitudinal factors that serve as exogenous variables in the model specification. These constructs were explained in detail earlier. All the indicators used to define the latent constructs were significant and loaded heavily on their designated latent constructs following a varimax rotation. The CFA results were suppressed and are not presented here in detail in the interest of brevity. It should be noted that factor loadings are all intuitive, and the latent constructs capture a range of preferences that are likely to influence an individual's propensity for vehicle ownership and use of ridehailing services.

Bivariate Model of Behavioral Outcomes

Table 2 presents model estimation results for the bivariate model of ordered behavioral outcomes. Ridehailing frequency is represented by the outcomes of never, rarely, monthly, and weekly. Vehicle availability is represented by the outcomes of none, vehicle deficient, and vehicle sufficient. The bivariate ordered probit modeling methodology was adopted in this study because frequency intervals across the ordinal outcomes may not be consistent. For example, in the case of ridehailing usage, the difference between never and rarely might not be the same as the difference between monthly and weekly. It

Table 2. Estimation Results for Endogenous Variables Within Each Segment

Explanatory variables (base category)		Segment 1 (ridehailing → vehicle availability)				Segment 2 (vehicle availability → ridehailing)			
		Ridehailing frequency (4-level: never to weekly)		Vehicle availability (3-level: none, deficient, sufficient)		Ridehailing frequency (4-level: never to weekly)		Vehicle availability (3-level: none, deficient, sufficient)	
		Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Endogenous variables	Ridehailing frequency	na	na	−0.49	−2.88	na	na	na	na
	Vehicle availability	na	na	na	na	−1.04	−5.58	na	na
Latent constructs	Time sensitivity	na	na	0.30	2.91	na	na	na	na
	Technology savviness	0.09	1.89	na	na	0.09	1.70	na	na
	Ridehailing perception	0.25	5.05	na	na	0.14	1.84	na	na
	Transit-oriented lifestyle	na	na	−0.43	−5.05	0.09	1.62	−0.22	−3.56
	Individual characteristics								
Age (*)	18–40 years	na	na	na	na	na	na	−0.86	−4.14
	65 years or older	na	na	na	na	na	na	0.57	4.31
	71 years or older	−0.40	−3.82	na	na	−0.56	−2.53	na	na
Education (<bachelor's degree)	Higher education	0.19	2.88	0.16	1.54	0.24	3.00	na	na
Race (not White or Caucasian)	White or Caucasian	na	na	0.32	2.92	na	na	0.14	1.46
Ethnicity (not Hispanic)	Hispanic	na	na	−0.20	−1.65	na	na	−0.20	−1.49
Employment (*)	Worker	na	na	0.28	2.34	na	na	0.39	3.23
	Nonworker	−0.22	−3.10	na	na	−0.29	−3.08	na	na
Household and other characteristics									
Household income (*)	Less than $25,000	na	na	−0.61	−4.67	na	na	na	na
	Less than $50,000	na	na	na	na	−0.19	−2.14	na	na
	$100,000 or more	na	na	0.40	2.63	na	na	na	na
	$150,000 or more	0.64	8.00	na	na	0.50	4.42	na	na
Household size (>1)	One	0.11	1.62	na	na	na	na	na	na
Housing unit type (other)	Stand-alone home	na	na	0.41	2.71	na	na	0.25	1.86
	Apartment	0.49	6.28	na	na	0.28	2.46	na	na
Population density (high)	Low (<3,000 person/mi^2)	−0.19	−3.15	na	na	na	na	na	na
City (Austin, Phoenix, Tampa)	Atlanta	na	na	na	na	na	na	0.42	4.28
Commute distance (0 or 5 +)	>0 to 5 mi	0.45	5.60	na	na	na	na	na	na
Thresholds	1|2	−0.30	−3.46	−1.95	−6.09	−2.62	−5.67	−4.22	−0.37
	2|3	1.13	13.30	−1.82	−5.36	−1.37	−2.76	0.48	2.32
	3|4	2.14	22.11	na	na	−0.48	−0.89	na	na
Correlation	Ridehailing frequency	na	na	0.32	1.43	na	na	0.50	2.89

Note: coef. = coefficient; t-stat = *t*-statistic; na = not applicable.

*Base category is not identical across the model equations and corresponds to all omitted categories.

Goodness-of-fit measures: adjusted ρ^2 = 0.147; Bayesian information criterion = 5135.04; log-likelihood (joint model) = −4901.47; log-likelihood (constants-only model) = −5,746.48.

Average probability of correct prediction: joint model = 0.285; constants-only model = 0.215.

was therefore necessary to adopt a methodology capable of accommodating this aspect of the ordered choice variables of interest. The bivariate ordered probit model is capable of reflecting differential intervals across choice outcomes through the use of threshold values that are estimated together with coefficients associated with the explanatory variables. The table shows the coefficient estimates for each of the two latent causal segments. In both segments, the endogenous variables depicted a significant inverse (negative) relationship, suggesting that higher vehicle availability was associated with a lower level of ridehailing frequency, and vice versa. These relationships were significant (in either causal direction), behaviorally intuitive, and consistent with previous findings (*8–10, 12*).

All other results were behaviorally intuitive, with largely consistent indications between the two segments. In the segment in which ridehailing affected vehicle availability, time sensitivity was found to have a positive influence on the propensity for higher vehicle availability. This finding echoed the notion that time-sensitive individuals who feel rushed are likely to prefer a higher level of access to an automobile, which is generally the fastest mode in the metropolitan areas where the survey was conducted. Furthermore, in both segments, technology savviness and a positive perception of ridehailing services enhanced the tendency toward using ridehailing services more frequently. Similar findings are reported in the literature (*5*, *21*). A transit-oriented lifestyle was associated with a lower level of vehicle availability, consistent with the findings reported by Cervero (*22*), and positively influenced ridehailing frequency in the segment in which vehicle availability affected ridehailing frequency.

Among individual characteristics, younger individuals (18 to 40 years) showed a lower tendency toward vehicle availability in the segment in which vehicle availability affected ridehailing. The older age group (71 + years) exhibited a lower propensity for ridehailing frequency, consistent with the notion that ridehailing users tend to be younger (*6*). Also consistent with prior research was the finding that higher education levels were associated with a tendency toward a higher frequency of ridehailing use (*9*). In the segment in which ridehailing affected vehicle availability, higher education levels were associated with a greater predisposition to higher vehicle availability. Whites had a greater tendency toward higher vehicle availability levels in both causal segments, whereas Hispanics had a lower tendency; prior research has also documented these racial differences (*12*, *23*). Workers were likely to prefer higher vehicle availability (presumably for commuting needs), whereas nonworkers exhibited a lower propensity for frequent ridehailing use—aligned with the findings reported previously (*24*, *25*).

In both segments, income effects echoed prior research (*25*). A lower income level (i.e., less than \$50,000 per year) was associated with lower levels of ridehailing frequency—a finding consistent with the literature (*9*). The highest income category (\$150,000 or more per year) exhibited a positive association with higher ridehailing usage, whereas the second-highest income bracket (\$100,000 or more per year) was associated with higher levels of vehicle availability. Single persons were more likely to use ridehailing, consistent with earlier findings (*10*). Stand-alone home residents were likely to have higher levels of vehicle availability, whereas individuals in apartments (presumably in higher-density locales) tended to embrace higher levels of ridehailing use. Low-density living was associated with lower levels of ridehailing use, whereas those with short commutes were likely to adopt higher levels of ridehailing use, confirming previous findings (*15*). Residents of Atlanta appeared to have a tendency toward higher levels of vehicle availability, but this finding appeared only in the segment in which vehicle availability affected ridehailing frequency.

The correlations between the two outcomes were positive in both segments, possibly indicating underlying correlated unobserved factors that favor private vehicle usage (personal cars as well as ridehailing vehicles). In contrast to transit and other nonmotorized modes, people generally preferred to travel in private vehicles owing to the greater convenience, comfort, and efficiency (*26*). The finding that this correlation was statistically significant and larger in Segment 2 (i.e., vehicle availability influences ridehailing frequency) also highlighted the underlying tendency toward the auto mode. This result speaks not only to the importance of the self-selection effect but also to the that of joint modeling. If positive correlations are ignored, the unexplained error correlation between the two variables will be included in the direct effect of one outcome on another (depending on which causal direction is considered). As a result, the magnitude of the negative impact of ridehailing frequency on vehicle availability (or vice versa) will be underestimated by independent model systems that ignore error correlation. The direct impacts estimated in this joint model system were thus the "true" (cleansed) effects of one outcome on the other, after controlling for the self-selection effect arising from unobserved factors that affected both outcome variables. From a goodness-of-fit measures standpoint, the proposed latent segmentation model was found to offer a significantly better fit than the corresponding naïve model system. This further reinforced the case for a joint model specification when examining interrelated mobility choices such as ridehailing use and vehicle availability.

Characteristics and Size of the Latent Segments

To probabilistically assign individuals to a causal structure, a binary latent market segmentation model was estimated. In the interest of brevity, the estimation results for this binary logit model are not presented in tabular form. Table 3 offers a detailed description of the segment profiles, thus obviating the need to present the estimation results explicitly (they essentially mirror the profiles in Table 3). This section, therefore, focuses on presenting the latent segment profiles.

Each segment size is reported at the bottom of Table 3. It is noteworthy that the majority (58%) of the observations were probabilistically assigned to the market segment in which ridehailing frequency affected vehicle availability. The remainder were assigned to the segment in which vehicle availability affected ridehailing frequency. This was counter to what is often represented in transportation demand forecasting models in practice, which generally tend to predict mode choice (including ridehailing use) as a function of vehicle ownership levels. Although vehicle ownership is affected by composite modal accessibility measures (such as logsums, which presumably reflect the presence of ridehailing services as well), these measures rarely (if ever) capture the frequency of ridehailing use. As a result, models do not reflect the influence of the extent of ridehailing use on household vehicle ownership. Both segments had a sizable proportion of sample observations, reflecting the need to incorporate multiple causal structures (reflecting different market segments) in transportation demand forecasting models (as opposed to assuming a single causal structure for all agents in the population).

Table 3 also shows variations of the two segments by demographic attributes. In general, attributes with substantial differences in the table appeared statistically significant in the binary segmentation model. The first broad numeric column, "Percent within segment," provides the split of a variable within each segment; thus, within the first segment in which ridehailing frequency affected vehicle availability, 56.2% were women, and 43.8% were men. Within the second segment (vehicle availability affected ridehailing frequency), the corresponding split between women and men was 58.4% and 41.6%, respectively. This indicated that women populated Segment 2 more than men. This can also be seen in the entries corresponding to the column titled "Percent within attribute." This showed that 57.1% of women belonged to Segment 1 (compared with 59.3% of men), whereas 49.2% of women belonged to Segment 2 (compared with 40.7% of men). Other entries may be similarly interpreted.

According to our results, age was also a distinguishing characteristic between the two segments. While 40.6% of individuals following the pattern in which ridehailing frequency affected vehicle availability fell in the younger age group of 18 to 40 years, the corresponding percentage for the other segment was lower at 34%. This is intuitive since younger individuals are more likely to embrace new mobility options. They were early adopters of ridehailing services and are likely to have used such services frequently enough and for a long enough duration to influence their decisions about vehicle ownership. Such differences are discernible throughout the table.

Other variables depicting key differences between the two segments included education, household income, household size, presence of children, housing unit type, and household vehicle ownership itself. All of these constitute variables that may be used to define market segments so that the appropriate causal structure can be applied in demand forecasting models. Consistent with historical evidence on who has tended to be early and more frequent adopters of ridehailing services, this study found that the market segment in which ridehailing frequency influenced vehicle availability exhibited higher shares of individuals who were highly educated and affluent, lived in small households, resided in apartments, and owned fewer vehicles. If one were to examine the percentages within segments, 67% of the market segment in which ridehailing frequency affected vehicle availability had a bachelor's degree or higher, as opposed to a smaller 57.7% for the market segment in which vehicle availability affected ridehailing frequency. Furthermore, 21.7% of those in the market segment in which ridehailing frequency affected vehicle availability fell in the income category of $150,000 or higher; this percentage was 15.1% for the other segment.

Nearly 80% of individuals in the segment in which ridehailing frequency affected vehicle availability belonged to one- or two-person households; the corresponding percentage for the other segment was 33%. Similar differences can be seen with respect to the presence of children (14.8% for the segment in which ridehailing frequency affected vehicle availability, but 42.8% for the other segment). In general, this study found that larger households with children in stand-alone housing units in suburban locales were more likely to embrace vehicle ownership-oriented lifestyles (because of their household mobility needs, patterns, and constraints), and this consequently affected the use of ridehailing services. These findings were consistent with expectations and demonstrated the importance of reflecting multiple causal structures in transportation demand forecasting models.

Discussion and Conclusions

This study was concerned with the complex interrelationship between ridehailing service usage and vehicle ownership. There were essentially two plausible (causal) relationships between these variables, and this study attempted to determine the degree to which these two

Table 3. Profiles of the Two Latent Market Segments

Attributes		Percent within segment		Percent within attribute		
		Segment 1 RF → VA	Segment 2 VA → RF	Segment 1 RF → VA	Segment 2 VA → RF	Overall sample, %
Individual characteristics						
Gender	Female	56.2	58.4	57.1	42.9	57.1
	Male	43.8	41.6	59.3	40.7	42.9
Age	18–40	40.6	34.0	62.3	37.7	37.8
	41–60	25.2	40.8	46.1	53.9	31.8
	61 or older	33.7	24.6	65.5	34.5	29.9
Education	High school or less	7.2	10.4	49.1	50.9	8.5
	Some college or technical school	26.0	31.7	53.2	46.8	28.4
	Bachelor's degree or higher	66.6	57.7	61.5	38.5	62.9
Race	Asian	8.2	10.1	53.1	46.9	9.0
	Black	8.3	7.1	61.6	38.4	7.8
	White or Caucasian	72.3	69.2	59.1	40.9	71.0
	Other	11.2	13.6	53.3	46.7	12.2
Employment	Worker	63.2	66.0	57.0	43.0	64.4
	Nonworker	36.8	34.0	60.0	40.0	35.6
Household characteristics						
Household income	Less than \$50,000	25.4	24.4	59.0	41.0	25.0
	\$50,000 to \$99,999	30.7	37.8	53.0	47.0	33.7
	\$100,000 to \$149,999	21.7	21.7	58.0	42.0	21.7
	\$150,000 or more	21.7	15.1	66.5	33.5	18.9
Household size	One	27.7	12.1	76.0	24.0	21.1
	Two	51.6	20.4	77.8	22.2	38.5
	Three or more	20.7	67.5	29.9	70.1	40.3
Household children	Zero	85.2	57.2	67.4	32.6	73.5
	One or more	14.8	42.8	32.4	67.6	26.5
Housing unit type	Stand-alone home	65.6	76.0	54.5	45.5	69.9
	Apartment	24.5	16.3	67.5	32.5	21.1
	Other	8.5	6.5	64.5	35.5	7.7
Household vehicle	Zero	4.7	2.7	70.5	29.5	3.9
	One	28.1	17.6	68.9	31.1	23.7
	Two or more	67.1	79.6	53.9	46.1	72.4
Other characteristics						
Population density	Low ($<$3,000 person/mi^2)	48.7	51.1	56.9	43.1	49.7
	High ($\geqslant$3,000 person/mi^2)	51.3	48.9	59.2	40.8	50.3
City	Atlanta	31.7	27.9	61.2	38.8	30.1
	Austin	32.4	32.3	58.1	41.9	32.3
	Phoenix	29.2	32.1	55.8	44.2	30.4
	Tampa	6.7	7.7	54.7	45.3	7.2
Segment size		Percent		58.1	41.9	100
		N		1,828	1,318	3,146

Note: RF = ridehailing frequency; VA = vehicle availability.

causal relationships coexisted in a population. In addition, the study sought to determine the profiles of the market segments following the two different causal structures. Because the causal relationship was not directly observable, a latent segmentation modeling approach was adopted. This approach allowed individuals to be probabilistically assigned to different causal market segments based on their attributes. A joint bivariate ordered probit model of ridehailing frequency and household vehicle availability was estimated, which incorporated the two plausible causal structures, one in which ridehailing frequency affects vehicle ownership and the other in which the opposite causal direction exists.

The majority of the sample (58%) followed the causal structure in which ridehailing frequency affected vehicle availability. The two latent market segments were found to differ substantially with respect to age, income, household size, housing unit type, and presence of children. Two key conclusions may be drawn from these findings. First, the two causal structures were prevalent in this particular sample to a substantial degree. Although it may be acceptable to ignore a specific causal structure if it is rare, neither causal structure could be ignored in this empirical context. Second, certain demographics (young, highly educated, affluent, adults in small households with no children and residing in apartments) appeared to have used ridehailing services frequently enough and for a duration long enough to have had an impact on their vehicle ownership.

This suggests that ridehailing services do exhibit the potential to (negatively) influence the levels of vehicle ownership in the future (as the services continue to grow). This study lends credence to the notion that a future characterized by MaaS may indeed see lower levels of private auto ownership as households become increasingly comfortable with downsizing their private vehicle fleet. At the same time, however, there was a sizable segment of the population for whom vehicle ownership levels had affected the degree to which they used ridehailing services. Targeted marketing campaigns and interventions that enhance the ability to embrace ridehailing services may help accelerate a future encompassing lower vehicle ownership; such campaigns should target older individuals and larger households (with children) residing in stand-alone housing units in suburban locales.

The study findings also indicated the need to reflect multiple causal structures in transportation demand forecasting models. Model systems that are based on a single causal structure (in which vehicle availability affects mode choice and ridehailing usage) do not reflect the structural heterogeneity prevalent in the population. Model systems need to be enhanced to define specific market segments in the population based on a multitude of socioeconomic dimensions. Furthermore, interrelated mobility choices should be modeled jointly with explicit accounting for error correlations to enable computation of the true effect between the choice variables. Through a market segmentation approach that employs joint model specifications, it will be possible to simultaneously reflect the alternative causal structures driving mobility choices, more accurately reflect true behavioral phenomena at play, obtain more reliable estimates of policy impacts/effects, and target interventions more effectively.

It is important to note that the study findings should be interpreted with caution because all of the analysis performed in this study was based on cross-sectional data, which are not necessarily ideal for investigating causal relationships between variables whose impacts on one another inevitably play out over time. This study was therefore limited to exploring contemporaneous causality, which refers to situations in which individuals make choices at a certain point depending on the context, situation, and conditions that exist at that time. To truly determine whether a change in one variable precedes or succeeds a change in another variable, behaviors and exogenous factors need to be tracked over a period of time. Future research should aim to collect and utilize longitudinal data to further explore the cause-and-effect relationship between ridehailing adoption and vehicle ownership and to verify the long-term validity of the study findings. In addition, future research could employ model systems such as that presented in this study to forecast ridehailing use and vehicle availability under various hypothetical socioeconomic, modal, and policy scenarios, with a view to demonstrating the efficacy of model systems that explicitly reflect population heterogeneity in causal relationships.

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Author Contributions

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

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ORCID iDs

Irfan Batur https://orcid.org/0000-0002-8058-2578
Aupal Mondal https://orcid.org/0000-0001-7724-7261
Chandra R. Bhat https://orcid.org/0000-0002-0715-8121
Ram M. Pendyala https://orcid.org/0000-0002-1552-9447

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