

Assessing the Impact of Ridehailing Service Use on Bus Ridership: A Joint Modeling Framework Accounting for Endogeneity and Latent Attitudes

Irfan Batur

Arizona State University
School of Sustainable Engineering and the Built Environment
660 S. College Avenue, Tempe, AZ 85287-3005
Email: ibaturo@asu.edu

Katherine E. Asmussen

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: kasmussen29@utexas.edu

Aupal Mondal

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: aupal.mondal@utexas.edu

Tassio B. Magassy

WSP USA
30 N Lasalle St, Chicago, IL 60602
Email: tassio.magassy@wsp.com

Sara Khoeini

WSP USA
1230 W Washington St #405, Tempe, AZ 85281
Email: skhoeini@asu.edu

Chandra R. Bhat

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712
Email: bhat@mail.utexas.edu

Ram M. Pendyala (corresponding author)

Arizona State University
School of Sustainable Engineering and the Built Environment
660 S. College Avenue, Tempe, AZ 85287-3005
Email: ram.pendyala@asu.edu

ABSTRACT

Transit ridership has been on the decline for several years, even prior to the onset of the COVID-19 pandemic. As transit agencies look to the future and contemplate how they can enhance their service to recover and grow ridership, there is a critical need to better understand the contribution of various factors to the decline in transit ridership. One key contributing factor is the rise of ridehailing services and its impact on transit use. This study aims to provide a comprehensive and holistic assessment of the impacts of ridehailing service use on transit ridership while controlling for a host of socio-economic, demographic, and attitudinal factors. Using detailed survey data collected in four automobile-centric metropolitan areas of the US, this study simultaneously models the frequency of using ridehailing services and the extent to which an individual has changed bus use due to ridehailing. The model system is estimated using the Generalized Heterogeneous Data Model (GHDM) methodology. Descriptive statistics as well as model estimation results indicate that ridehailing use frequency is significantly associated with a decrease in bus use, suggesting that ridehailing serves as a substitute for bus use (more than it serves as a complement). The findings suggest that transit agencies need to explore strategies and partnerships that leverage ridehailing services to better complement transit usage.

Keywords: ridehailing service, transit use, mode substitution effects, attitudes and behaviors, integrated model of behavior

1. INTRODUCTION

Transit has been experiencing a decline in ridership over the past decade in the United States (Boisjoly et al., 2018). While the COVID-19 pandemic has undoubtedly played havoc with transit ridership in recent years, the fact remains that transit ridership was on the decline even prior to the onset of the pandemic (Graehler et al., 2019). As transit agencies look to the future and contemplate how they can enhance their service to stem the tide, there is a critical need to better understand the contribution of various factors to the decline in transit ridership. Transit remains a mode of transportation that is critical to the movement of people, particularly serving those who may not have access to (or be able to use) an automobile. During the pandemic, it became apparent that transit is a critical mode of transportation helping essential frontline workers to get to and from their jobs.

There are a number of reasons that have likely contributed to the decline in transit ridership over the past decade in particular. In most markets across the US, transit is not competitive when compared to the private automobile. As such, except for small shares of individuals, many travelers naturally gravitate toward the use of the automobile for meeting mobility needs. With rising incomes and greater employment opportunities available following the great recession, it is to be expected that individuals would acquire private automobiles for transportation purposes. During the years preceding the pandemic, the nation saw record numbers of new and used vehicles being bought and sold in the US (Woodall, 2016), clearly suggesting that the appetite for automobile-oriented private mobility continues unabated. Other reasons that contribute to transit decline include the continued sprawl of land use patterns (both residential and employment) that render transit use challenging, reconfiguration of transit service in efforts to attract choice riders (which often occurs at the expense of serving more captive riders), and the affordability and reliability of the personal automobile mode (Taylor et al., 2009; Chakraborty and Mishra, 2013; Boisjoly et al., 2018).

In addition to the reasons for transit decline noted in the prior paragraph (which have existed for decades now), a more recent phenomenon that may have adversely impacted transit ridership is the rise of ridehailing services (e.g., Uber and Lyft) that provide on-demand curb-to-curb mobility through the convenience of a smartphone app. The app allows users to summon rides and automates the process of tracking and paying for rides. These services have gained considerable traction over the past decade in cities around the world thanks to their convenience and affordability (relative to traditional taxi transportation).

Ridehailing services may impact transit patronage in a number of ways. An individual may utilize ridehailing services instead of transit, thus creating a substitution effect with transit losing riders to ridehailing services. On the other hand, a traveler may use ridehailing services to connect to and from transit stations/stops, essentially fulfilling first- and last-mile connectivity that would enable convenient transit access and egress. In this scenario, transit would gain ridership thanks to the availability of ridehailing services. And finally, ridehailing services may not impact transit ridership at all; it could take the place of another mode of transportation or simply generate a net new trip that would not have been undertaken otherwise. There may be other ways in which ridehailing services and transit interact with one another, especially with a number of transit agencies establishing partnerships with ridehailing service providers (e.g., APTA, 2020; Shaheen and Cohen, 2020), but the fact remains that the relationship generally comes down to one of substitution, complementarity, or no-effect.

Explorations of the relationship between ridehailing service and transit use have been undertaken and documented in the literature. Some studies point to instances where ridehailing has

served to enhance transit connectivity and usage, but in most instances, it is clear that ridehailing is a transit substitute. Ridehailing also substitutes for the use of other modes (most notably, traditional taxi and personal automobile), but most survey research to date clearly shows that ridehailing serves as a substitute for transit. However, past studies exploring the relationships between ridehailing and transit use have largely been descriptive in nature (e.g., Rayle et al., 2016; Clewlow and Mishra, 2017; Young and Farber, 2019) or have relied on models that do not fully account for the complex relationships and attitudinal constructs that govern the impact of ridehailing on transit use (e.g., Hall et al., 2018; Gehrke et al., 2019; Dong, 2020).

This study attempts to provide a more comprehensive assessment of the impacts of ridehailing service use on transit ridership while controlling for a host of socio-economic, demographic, and attitudinal factors. Using detailed survey data collected in four automobile-centric metropolitan areas of the US, namely, Phoenix, Austin, Atlanta, and Tampa, this study simultaneously models the frequency of using ridehailing services and the extent to which an individual has changed use of bus services due to ridehailing service usage. The frequency of ridehailing use and the change in bus usage are treated as endogenous variables, with the frequency of ridehailing use directly affecting bus use change. In addition, the simultaneous equations model incorporates latent attitudinal constructs that capture modal and lifestyle preference of the survey respondents, thus accounting for the effects of attitudes that are likely to influence the nature of the relationships of interest. The model is estimated in a single step using the Generalized Heterogeneous Data Model (GHDM) framework developed by Bhat (2015); this methodological framework enables the efficient estimation of joint model systems that incorporate error correlations across endogenous variables, thus accounting for the presence of correlated unobserved attributes that may be simultaneously affecting multiple endogenous variables. The study focuses exclusively on bus use change because metropolitan areas differ considerably with respect to the presence and nature of rail service in their transportation ecosystem (while bus service tends to be a rather ubiquitous transit mode available in virtually all markets). Bus use may increase (complementarity), decrease (substitution), or experience no change as a result of ridehailing service use.

The remainder of this paper is organized as follows. The next section presents a brief review of the literature focusing on related work. The third section provides a detailed description of the data set and dependent variables of interest. The fourth section presents the modeling framework and the modeling methodology adopted in this study. The fifth section presents model estimation results, together with average treatment effects. The sixth section offers a discussion of the implications of the findings and presents concluding thoughts.

2. LITERATURE REVIEW

A review of the literature suggests that the body of evidence on the relationship between ridehailing use and transit ridership is growing, particularly as concerns about transit ridership recovery in the post-pandemic era dominate the headlines. There is, however, a vast body of literature dedicated to understanding the characteristics of ridehailing service users. In many geographical contexts, it has been found that ridehailing users tend to be young, affluent, and highly educated (Tirachini, 2019). The frequency of ridehailing use tends to be more context dependent, with some studies showing positive associations of ridehailing use frequency with younger age and higher education (Sikder 2019; Tirachini and del Rio, 2019; Vinayak, 2018). The influence of other socio-demographic attributes tends to be more mixed. For instance, in the US context, Sikder (2019) found that females exhibit a lower ridehailing use frequency, while other

studies did not find any gender effect. On the contrary, a recent study (von Behren et al., 2021) focusing on China found that women are more likely to use ridehailing services for commuting than men. Similar results revealing either the absence of a significant effect or conflicting findings are also reported for income, race, and employment status, both within the US and other countries (Circella et al., 2018; Vinayak, 2018; Sikder, 2019; Tirachini and del Rio, 2019; Atkinson-Palombo et al., 2019; von Behren et al., 2021; Gomez et al., 2021). This is not to say that the evidence is inconclusive, but is suggestive of a strong context-dependent aspect to the nature of the relationships. There is also limited knowledge about the lifestyles, perceptions, and attitudes of ridehailing users (Vinayak et al., 2018; Gomez et al., 2021) and how such variables impact frequency of use of such services.

As noted earlier, there is a growing strand of research focused on the relationship between ridehailing services and public transit, aimed at investigating whether these two transportation modes are in direct competition. Some studies have analyzed this potential competition using aggregated trip data at different geographical levels, primarily in North America and China (Lavieri et al., 2018; Ghaffar et al., 2020; Ngo et al., 2021; Hall et al., 2018; Diab et al., 2020; Bi et al., 2021; Liao, 2021). Results show that the relationship between ridehailing services and public transit varies depending on the availability and service levels of different transit modes and locational context (Hall et al., 2018; Diab et al., 2020; Ghaffar et al., 2020; Ngo et al., 2021; Li et al., 2021). While the aggregate data analysis provides rich insights into the overall nature of the relationship between these two modes, these studies often lack rich information or insights about user characteristics, thus rendering it challenging to identify groups who use ridehailing as a substitute for transit versus those who use ridehailing services a complement to transit. Hence, survey data based studies, such as this one, could provide richer insights into the nature of the relationship between these two modes of transportation for different groups.

In survey-based studies, the impact of ridehailing services on public transit is primarily assessed by asking respondents how they would have made their last ridehailing trip if the service was not available (Rayle et al., 2016; Clewlow and Mishra, 2017; Alemi et al., 2018; Henao and Marshall, 2018; Acheampong et al., 2020). The percentage of respondents who would have used transit varies based on the survey location, generally falling between 10 and 40 percent (Gehrke et al., 2019; Bansal et al., 2020), indicating that differences exist between geographical contexts (dependent on level of transit service and coverage). In a study by Clewlow and Mishra (2017), respondents from eight US metropolitan areas were asked about their transit use after adopting ridehailing services. The authors found that the respondents decreased their bus and light rail usage, while increasing their heavy rail usage, albeit to a smaller extent. A few researchers have also conducted “stated-choice” experiments, where respondents choose between ridehailing and transit for hypothetical trips with varying costs, travel times, and wait times (Dong, 2020; Dong et al., 2021).

This study aims to add to the body of knowledge on the impacts that ridehailing use has had on transit use. Many studies conducted thus far are rather descriptive in nature, with only a few utilizing rigorous econometric modeling frameworks to examine the role of socio-demographic and built-environment factors in shaping the relationship between ridehailing and transit use (e.g., Gehrke et al., 2019; Loa et al., 2021; Dong et al., 2021). Also, many studies, with the exception of Clewlow and Mishra (2017), usually base their findings on only the most recent ridehailing trip, leading to limited generalizability of study findings to all ridehailing trips. Because these studies use questions that are binary in nature (whether they would have used/chosen transit or not), they only reveal the substitution effect of ridehailing services on transit, and do not

adequately account for potential complementarity or no-effect situations. Another issue is that several studies examining the relationship between the modes do not sufficiently differentiate between different modes of public transit when assessing the substitution impacts of ridehailing services, even though these services are found to affect bus and rail ridership differently (Ghaffar et al., 2020; Li et al., 2021). Finally, the influence of psycho-social factors such as lifestyles, perceptions, and attitudes of individuals in moderating the effects of ridehailing service use on public transit use is not well understood. These factors could play a significant role in determining whether an individual will increase, decrease, or keep their use of transit unchanged due to adoption of ridehailing services.

The current study aims to contribute to the understanding of the impact of ridehailing services on transit ridership by simultaneously accounting for the role of socio-economic variables, built environment and contextual variables, and attitudinal variables in shaping the nature of the relationship. The study considers the overall change in bus use due to ridehailing adoption and explicitly distinguishes between substitution, complementarity, and no-effect situations. Through a joint-modeling framework, the study sheds light on the impact and potential causality of the frequency of ridehailing use on bus use change while accounting for a host of socio-demographic and built environment attributes as well as psycho-social factors such as individual lifestyles, perceptions, and attitudes.

3. DATA DESCRIPTION

This section presents a brief description of the dataset used in this study. An overview of the survey and the sample characteristics is presented first; a more in-depth examination of the endogenous variables and attitudinal statements of interest in this study is presented second.

3.1. Characteristics of the Sample

In the Fall of 2019, a comprehensive survey was administered in four major metropolitan areas of the United States: Phoenix, Austin, Atlanta, and Tampa. All four areas are located in warmer climates of the country and are characterized by dispersed land use patterns and modest levels of transit service (and very low transit mode shares). The survey was aimed at collecting rich information about people's attitudes and perceptions towards emerging mobility services and transportation technologies besides their socio-economic, demographic, and routine activity-travel characteristics. The same survey instrument was administered in all four metropolitan regions, thus ensuring consistency in data collection. The sampling methodology had to be customized to some degree in each region to enhance the response rate. Respondents were recruited by sending invitations to hundreds of thousands of e-mail addresses and several thousand mailing addresses. The random set of e-mail and postal addresses was obtained from a commercial vendor. Individuals who completed the survey and provided all requisite information were provided a \$10 gift card as an incentive and token of appreciation. The complete sample across all four areas comprised 3,465 individuals. Full details about the survey and the sample are contained in a series of reports (Khoeini et al., 2021).

The analysis in this paper is focused on understanding the relationship between ridehailing service use (frequency) and change in bus use. As such, the analysis sample includes only the subset of individuals who actually use ridehailing services. All non-users and those who indicated their bus use changed, but not due to ridehailing use, were eliminated from the analysis sample. In addition, records with missing or obviously erroneous data were excluded from the analysis

sample. The final resulting analysis sample comprised 1,336 respondents. Table 1 shows the characteristics of this subsample of respondents.

TABLE 1 Socio-Economic and Demographic Characteristics of the Sample

<i>Individual characteristics (N = 1,336)</i>		<i>Household characteristics (N = 1,336)</i>	
Variable	%	Variable	%
Gender		Household annual income	
Female	60.4	Less than \$25,000	12.9
Male	39.6	\$25,000 to \$49,999	11.8
Age category		\$50,000 to \$74,999	16.3
18-30 years	37.7	\$75,000 to \$99,999	12.8
31-40 years	15.8	\$100,000 to \$149,999	21.2
41-50 years	15.3	\$150,000 to \$249,999	15.9
51-60 years	15.7	\$250,000 or more	9.1
61-70 years	10.5	Household size	
71+ years	5.0	One	22.3
Driver's license possession		Two	35.4
Yes	92.6	Three or more	42.3
No	7.4	Housing unit type	
Employment status		Stand-alone home	61.1
Student (part-time or full-time)	12.9	Condo/apartment	29.7
Worker (part-time or full-time)	58.8	Other	9.1
Both worker and student	14.1	Homeownership	
Neither worker nor student	14.1	Own	59.7
Education attainment		Rent	35.0
High school or less	7.2	Other	5.3
Some college or technical school	25.6	Vehicle ownership	
Bachelor's degree(s)	38.4	Zero	5.5
Graduate degree(s)	28.8	One	24.7
Race		Two	39.3
Asian or Pacific Islander	12.4	Three or more	30.5
Black or African American	8.7	Location	
Multi race	3.7	Atlanta, GA	34.2
Native American	0.6	Austin, TX	42.4
Other	1.5	Phoenix, AZ	16.7
White or Caucasian	73.2	Tampa, FL	6.7
Endogenous Variables			
Frequency of ridehailing service usage		Change in bus use due to ridehailing service	
Weekly	6.7	Increase	4.2
Monthly	25.8	No change	77.3
Rarely	67.4	Decrease	18.5

The sample characteristics show a level of variability that is appropriate for model development and estimation. Even though the sample characteristics may not perfectly mirror population census distributions, that does not present a problem in the context of a modeling effort of the kind undertaken in this paper. Females are over-represented, comprising just over 60 percent of the sample. The lowest age group depicts the highest presence in the sample, with 37.7 percent of the analysis sample falling into the 18-30-year age group. All other age groups are well represented in the sample. Nearly 93 percent of the respondents have a driver's license, nearly 59 percent are full or part-time workers, and about 14 percent are neither workers nor students. The sample depicts a high level of educational attainment with a little over 38 percent having a Bachelor's degree and about 29 percent having a graduate degree.

About 73 percent of the sample respondents are White, 12.4 percent are Asian or Pacific Islander, and 8.7 percent are Black. The income distribution shows a rich variation with a healthy representation of individuals in every income bracket. In terms of household size, 42.3 percent of individuals reported living in households with three or more people while 22.3 percent constituted single-person households. A little over 60 percent reside in stand-alone homes and nearly 30 percent reside in condo/apartment units. Nearly 60 percent own their home, while 35 percent are renters. Just about 5.5 percent of individuals report living in households with no vehicles; nearly 25 percent are in households with one vehicle; and 30.5 percent are residing in households with three or more vehicles. This distribution suggests that this is a sample with a high level of household vehicle availability. The sample is composed more heavily of individuals from the Austin and Atlanta areas due to a higher level of ridehailing service use in those areas.

3.2. Endogenous Variables and Attitudinal Indicators

Table 1 also depicts distributions of the behavioral endogenous variables of interest. Both, frequency of ridehailing service usage and change in bus use after adoption of ridehailing service, are ordered dependent variables with three categories each. It is found that about two-thirds of the sample uses ridehailing services rarely (less than monthly); just over one-quarter of the sample uses ridehailing services monthly; and only 6.7 percent use these services weekly. In terms of change in bus usage, only 4.2 percent report an increase in bus use due to the adoption of ridehailing services. On the other hand, 18.5 percent report a decrease in bus usage. Most individuals (77.3 percent) report no change in bus use due to ridehailing service usage.

One of the key objectives of the modeling exercise undertaken in this paper is to explicitly account for latent attitudinal constructs that may impact the endogenous variables of interest. The latent attitudinal constructs are endogenous variables themselves as well and are influenced by exogenous socio-economic and demographic characteristics. Three latent constructs are considered in this study. They are *pro-environment attitude (PEA)*, *mobility service perception (MSP)*, and *transit-oriented lifestyle (TOL)*. Each latent construct is captured using three attitudinal variables or indicators in the data set. These indicators are highly correlated with one another and constitute an important dimension of the latent construct. Figure 1 depicts the three stochastic latent constructs and their corresponding attitudinal indicators. In the interest of brevity, each and every attitudinal statement is not described in detail here as the distributions depicted in the figure are self-explanatory.

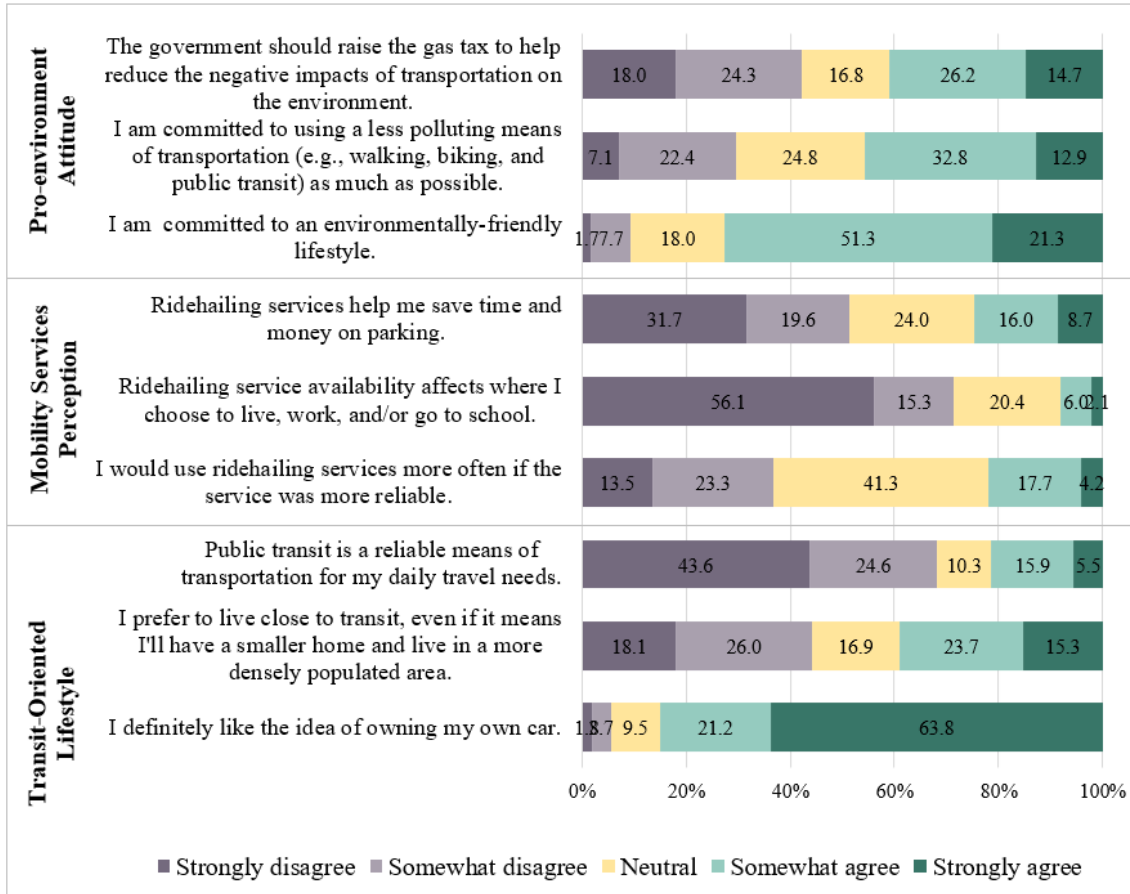


Figure 1 Distribution of Attitudinal Indicators of Latent Variables (N = 1,336)

Figure 2 presents a bivariate descriptive chart of the two dependent variables. The pattern suggests a relationship between the two dimensions of interest, but a multivariate modeling framework is needed to truly capture the relationship between these two behavioral phenomena while controlling for other socio-economic, demographic, and attitudinal variables. As expected, the greatest change in bus use occurs among those who use ridehailing services very frequently (weekly basis). The number of individuals who indicate that they use ridehailing weekly is small (N=90); within this group, nearly nine percent indicated that they increased bus use, but 40 percent indicated that they decreased their bus use as a result of ridehailing service usage. Among those who use ridehailing services more sparingly, nearly 80 percent report no change in bus use due to ridehailing. Only four percent increased bus use, while the remainder (16 percent of rare users and 19.4 percent of monthly users) decreased bus use. Clearly, frequency of ridehailing service usage does have implications for change in bus use, and the percentage of individuals decreasing bus use greatly exceeds the percent of individuals increasing bus use (due to ridehailing service usage). This is the first indication that ridehailing substitutes for, and takes away, bus ridership (more than it complements and adds to bus ridership).

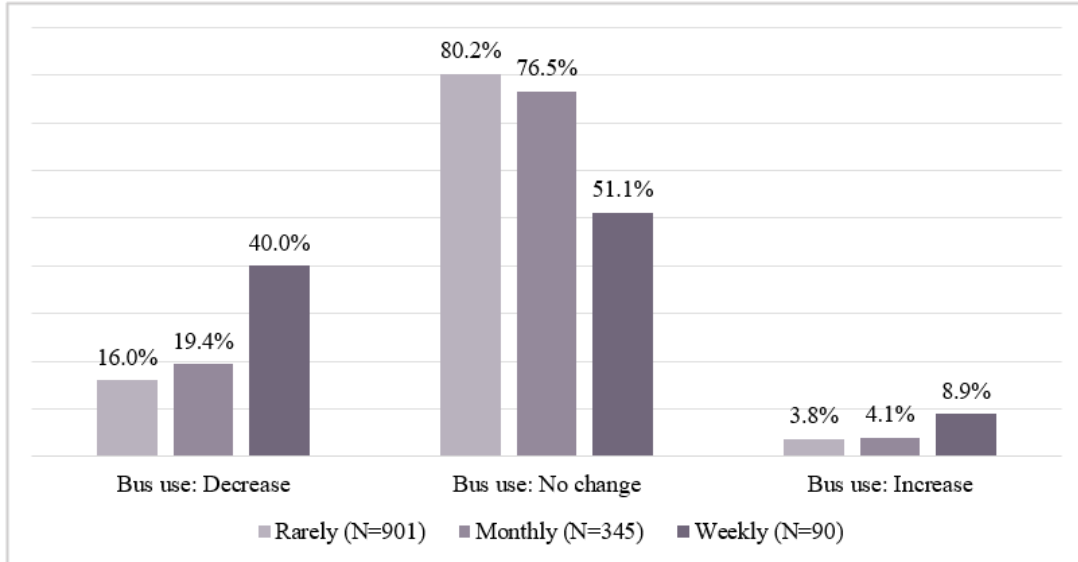


Figure 2 Bus Use Change by Ridehailing Services Usage Frequency (N = 1,336)

4. MODELING FRAMEWORK

This section presents the modeling framework and methodology. The modeling framework should be capable of accounting for multiple endogenous variables and the influence of latent attitudinal constructs (which are endogenous themselves). The overall model structure is presented first, while the model formulation and estimation methodology are presented second.

4.1. Model Structure

A simplified representation of the model structure is depicted in Figure 3. The analytic framework centers on developing a joint model of ridehailing service use frequency and bus use change. The determinants of the main outcome variables include individual-level variables spanning socio-economic, demographic, and household characteristics as well as attitudinal/lifestyle factors that are largely psycho-social factors. The factors are not directly observable but are treated as latent stochastic constructs revealed through an individual's responses to a set of attitudinal statements in the survey.

Exogenous variables include socio-economic and demographic variables together with select travel or mobility routines that may be treated as exogenous for purposes of this study. There is a direct effect between the two endogenous variables, with the frequency of ridehailing service use affecting change in bus use. Exogenous variables can directly influence the behavioral outcomes of interest. At the same time, they may also influence the endogenous variables through an intermediate set of latent attitudinal constructs. The three latent attitudinal constructs influence the endogenous variables and are themselves influenced by exogenous variables. As they are stochastic in nature, error correlations may be computed for the latent constructs; and by virtue of their stochasticity, they are able to engender an implied correlation between the two endogenous variables themselves. It is desirable to estimate the entire model structure in one step for purposes of parameter efficiency and representation of jointness in the behavioral outcomes of interest. The Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015) offers a computationally efficient and robust approach for parameter estimation. The estimation methodology is presented briefly in the next subsection.

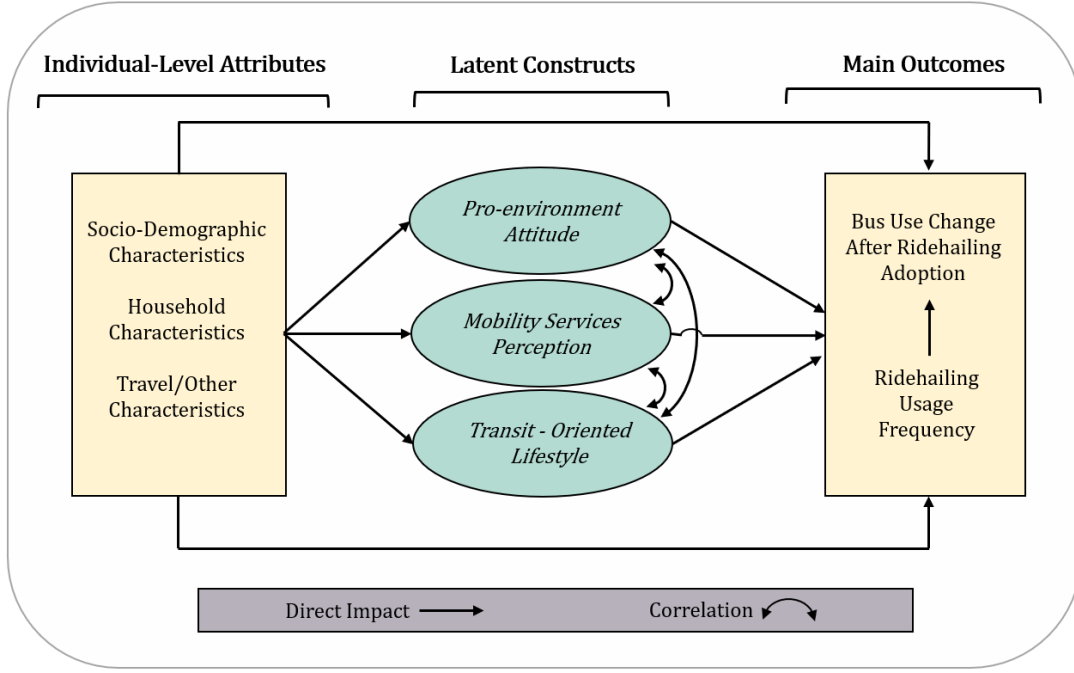


Figure 3 Modeling Framework

4.2. Model Estimation Methodology

As the outcomes as well as the indicators are ordinal in nature, the GHDM is formulated in this study exclusively for ordinal outcomes. Consider the case of an individual $q \in \{1, 2, \dots, Q\}$. Let $l \in \{1, 2, \dots, L\}$ be the index of the latent constructs and let z_{ql}^* be the value of the latent variable l for the individual q . z_{ql}^* is expressed as a function of its explanatory variables as,

$$z_{ql}^* = \mathbf{w}_{ql}^T \boldsymbol{\alpha} + \eta_{ql}, \quad (1)$$

where \mathbf{w}_{ql} ($D \times 1$) is a column vector of the explanatory variables of latent variable l and $\boldsymbol{\alpha}$ ($D \times 1$) is a vector of its coefficients. η_{ql} is the unexplained error term and is assumed to follow a standard normal distribution. Equation (1) can be expressed in matrix form as,

$$\mathbf{z}_q^* = \mathbf{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q, \quad (2)$$

where \mathbf{z}_q^* ($L \times 1$) is a column vector of all the latent variables, \mathbf{w}_q ($L \times D$) is a matrix formed by vertically stacking the vectors $(\mathbf{w}_{q1}^T, \mathbf{w}_{q2}^T, \dots, \mathbf{w}_{qL}^T)$ and $\boldsymbol{\eta}_q$ ($D \times 1$) is formed by vertically stacking $(\eta_{q1}, \eta_{q2}, \dots, \eta_{qL})$. $\boldsymbol{\eta}_q$ follows a multivariate normal distribution centered at the origin and having a correlation matrix of $\boldsymbol{\Gamma}$ ($L \times L$), i.e., $\boldsymbol{\eta}_q \sim MVN_L(\mathbf{0}_L, \boldsymbol{\Gamma})$, where $\mathbf{0}_L$ is a vector of zeros. The variance of all the elements in $\boldsymbol{\eta}_q$ is fixed as unity because it is not possible to uniquely identify a scale for the latent variables. Equation (2) constitutes the structural component of the framework.

Let $j \in \{1, 2, \dots, J\}$ denote the index of the outcome variables (including the indicator variables). Let y_{qj}^* be the underlying continuous measure associated with the outcome variable y_{qj} . Then,

$$y_{qj} = k \text{ if } t_{jk} < y_{qj}^* \leq t_{j(k+1)}, \quad (3)$$

where $k \in \{1, 2, \dots, K_j\}$ denotes the ordinal category assumed by y_{qj} and t_{jk} denotes the lower boundary of the k^{th} discrete interval of the continuous measure associated with the j^{th} outcome. $t_{jk} < t_{j(k+1)}$ for all j and all k . Since y_j^* may take any value in $(-\infty, \infty)$, we fix the value of $t_{j1} = -\infty$ and $t_{j(K_j+1)} = \infty$ for all j . Since the location of the thresholds on the real line is not uniquely identifiable, set $t_{j2} = 0$. y_j^* is expressed as a function of its explanatory variables and other observed dummy variable endogenous outcomes (only in a recursive fashion, if specified),

$$y_{qj}^* = \mathbf{x}_{qj}^T \boldsymbol{\beta} + \mathbf{z}_q^{*T} \mathbf{d}_j + \xi_{qj}, \quad (4)$$

where \mathbf{x}_{qj} is an $(E \times 1)$ vector of explanatory variables including a constant as well as including the possibility of other dummy variable endogenous outcomes. $\boldsymbol{\beta}$ $(E \times 1)$ is a column vector of the coefficients associated with \mathbf{x}_{qj} and \mathbf{d}_j $(L \times 1)$ is the vector of coefficients of the latent variables for outcome j . ξ_{qj} is a stochastic error term that captures the effect of unobserved variables on y_{qj}^* . ξ_{qj} is assumed to follow a standard normal distribution. Jointly, the continuous measures of the J outcome variables may be expressed as,

$$\mathbf{y}_q^* = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} \mathbf{z}_q^* + \boldsymbol{\xi}_q, \quad (5)$$

where \mathbf{y}_q^* $(J \times 1)$ and $\boldsymbol{\xi}_q$ $(J \times 1)$ are the vectors formed by vertically stacking y_{qj}^* and ξ_{qj} , respectively, of the J dependent variables. \mathbf{x}_q $(J \times E)$ is a matrix formed by vertically stacking the vectors $(\mathbf{x}_{q1}^T, \mathbf{x}_{q2}^T, \dots, \mathbf{x}_{qJ}^T)$ and \mathbf{d} $(J \times L)$ is a matrix formed by vertically stacking $(\mathbf{d}_1^T, \mathbf{d}_2^T, \dots, \mathbf{d}_J^T)$. $\boldsymbol{\xi}_q$ follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms), i.e., $\boldsymbol{\xi}_q \sim MVN_J(\mathbf{0}_J, \mathbf{I}_J)$. It is assumed the terms in $\boldsymbol{\xi}_q$ are independent because it is not possible to uniquely identify all correlations between the elements in $\boldsymbol{\eta}_q$ and all correlations between the elements in $\boldsymbol{\xi}_q$. Further, because of the ordinal nature of the outcome variables, the scale of \mathbf{y}_q^* cannot be uniquely identified. Therefore, the variances of all elements in $\boldsymbol{\xi}_q$ are fixed to one. The reader is referred to Bhat (2015) for further nuances regarding the identification of coefficients in the GHDM framework.

Substituting Equation (2) in Equation (5), \mathbf{y}_q^* can be expressed in the reduced form as

$$\mathbf{y}_q^* = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} (\mathbf{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q) + \boldsymbol{\xi}_q, \quad (6)$$

$$\mathbf{y}_q^* = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} \mathbf{w}_q \boldsymbol{\alpha} + \mathbf{d} \boldsymbol{\eta}_q + \boldsymbol{\xi}_q. \quad (7)$$

On the right side of Equation (7), $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ are random vectors that follow the multivariate normal distribution and the other variables are non-random. Therefore, \mathbf{y}_q^* also follows the multivariate normal distribution with a mean of $\mathbf{b} = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} \mathbf{w}_q \boldsymbol{\alpha}$ (all elements of $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ have a mean of zero) and a covariance matrix of $\boldsymbol{\Sigma} = \mathbf{d} \boldsymbol{\Gamma} \mathbf{d}^T + \mathbf{I}_J$, i.e.,

$$\mathbf{y}_q^* \sim MVN_J(\mathbf{b}, \boldsymbol{\Sigma}). \quad (8)$$

The parameters that are to be estimated are the elements of $\boldsymbol{\alpha}$, strictly upper triangular elements of $\boldsymbol{\Gamma}$, elements of $\boldsymbol{\beta}$, elements of \boldsymbol{d} and t_{jk} for all j and $k \in \{3, 4, \dots, K_j\}$. Let $\boldsymbol{\theta}$ be a vector of all the parameters that need to be estimated. The maximum likelihood approach can be used for estimating these parameters. The likelihood of the q^{th} observation will be,

$$L_q(\boldsymbol{\theta}) = \int_{v_1=t_{1yq1}-b_1}^{v_1=t_{1(yq1+1)}-b_1} \int_{v_2=t_{2yq2}-b_2}^{v_2=t_{2(yq2+1)}-b_2} \dots \int_{v_J=t_{JyqJ}-b_J}^{v_J=t_{J(yqJ+1)}-b_J} \phi_J(v_1, v_2, \dots, v_J | \boldsymbol{\Sigma}) dv_1 dv_2 \dots dv_J, \quad (9)$$

where, $\phi_J(v_1, v_2, \dots, v_J | \boldsymbol{\Sigma})$ denotes the probability density of a J dimensional multivariate normal distribution centered at the origin with a covariance matrix $\boldsymbol{\Sigma}$ at the point (v_1, v_2, \dots, v_J) . Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, the One-variate Univariate Screening technique proposed by Bhat (2018) was used for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

5. MODEL ESTIMATION RESULTS

This section presents the estimation results for the joint model system. The entire model structure was estimated in one step using the GHDM methodology. The factor loadings, effects of exogenous variables on the latent factors and behavioral dimensions of interest, and the relationship between the endogenous variables are estimated simultaneously, thus accounting for the jointness in the complex interrelationships that characterize ridehailing and bus use.

5.1. Latent Construct Model Components

Table 2 presents estimation results for the latent variable component of the model system. The table presents factor loadings for attitudinal indicators that define the latent constructs as well as model coefficients depicting the influence of exogenous variables on the latent constructs. As noted earlier, there are three latent constructs defined by three attitudinal indicators each. The factor loadings are all intuitive and significant, clearly indicating that they are appropriate indicators for the latent constructs defined in this study.

A host of exogenous variables influence the latent attitudinal constructs. It was found that there was no significant gender effect across all three latent constructs. This is somewhat inconsistent with findings reported in the literature (e.g., Lavieri and Bhat, 2019; Sikder, 2019; von Behren et al., 2021), but is a result in this study that held fast under alternative model specifications. Younger individuals are more likely to view mobility services positively, consistent with earlier findings in the literature that have consistently shown that younger individuals use mobility services more than others (e.g., Rayle et al., 2016; Alemi et al., 2018; Sikder, 2019). Older individuals exhibit a higher degree of pro-environment attitude and a lower degree of transit-oriented lifestyle, consistent with the literature (e.g., Cervero, 2007; Wiernik et al., 2013; Lavieri and Bhat, 2019; Sharda et al., 2019). In general, those in the middle age groups are in a lifecycle stage where concerns about employment, household obligations, childcare, and financial security tend to be greater, and hence less emphasis is placed on environmental and transit-oriented lifestyles (Wiernik et al., 2013; McCarthy et al., 2017).

TABLE 2 Determinants of Latent Variables and Loadings on Indicators (N = 1,336)

Explanatory Variables (base category)	Structural Equations Model (SEM) Component					
	Pro-environment Attitude		Mobility Services Perception		Transit-oriented Lifestyle	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics						
<i>Age (*)</i>						
18-30 years	—	—	0.59	16.47	—	—
18-40 years	-0.14	-6.29	—	—	—	—
31-65 years	—	—	—	—	-0.37	-16.13
<i>Education (*)</i>						
High school or less	—	—	—	—	0.32	9.29
Graduate degree(s)	0.31	13.61	—	—	—	—
<i>Race (White)</i>						
Non-White	—	—	0.66	18.46	—	—
<i>Employment status (not a student)</i>						
Student	0.38	13.91	—	—	—	—
Household characteristics						
<i>Household income (*)</i>						
Up to \$25,000	—	—	0.34	8.43	—	—
Up to \$50,000	—	—	—	—	0.50	20.98
\$100,000 to \$150,000	-0.25	-10.73	—	—	—	—
\$100,000 or over	—	—	-0.34	-11.13	—	—
<i>Household structure (not a nuclear family)</i>						
Nuclear family	—	—	—	—	-0.39	-15.48
Correlations between latent constructs						
Pro-environment attitude	1	—	0.68	4.61	0.95	7.56
Mobility services perception			1	—	0.80	5.64
Transit-oriented lifestyle					1	—
Attitudinal Indicators						
Loadings of Latent Variables on Indicators (Measurement Equations Model Component)						
The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.	0.62	22.47				
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	0.91	24.07				
I am committed to an environmentally-friendly lifestyle.	0.45	18.18				
Ridehailing services help me save time and money on parking.			0.66	17.67		
Ridehailing service availability affects where I choose to live, work, and/or go to school.			0.42	17.81		
I would use ridehailing services more often if the service was more reliable.			0.32	17.25		
Public transit is a reliable means of transportation for my daily travel needs.					0.80	26.98
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.					0.65	26.01
I definitely like the idea of owning my own car.					-0.58	-22.83

Note: Base categories for attributes (*) are the excluded categories not appearing in the table.

As expected, a higher education level is associated with a greater degree of pro-environment attitude, similar to findings reported by Kang et al. (2021) and Blazanin et al. (2021). Students depict a higher level of pro-environment attitude than others. At the same time, those with a lower education level (high school or less) appear more transit oriented than others; this, however, is largely because these individuals are in a lower income bracket and depend more heavily on transit for their mobility (leading to a greater inclination towards a transit oriented lifestyle). The household income and structure effects are intuitive as well. Lower income individuals depict a more positive perception of mobility services because they use them for mobility and find them convenient and affordable to do so (at least for short trips). Lower income individuals are also more inclined to be transit oriented. On the other hand, higher income individuals – who tend to own and use cars more than other groups – are less pro-environment and less favorable about mobility services (largely because they do not have a need to use mobility services on any regular basis). These findings are consistent with those reported in the literature (e.g., Cervero, 2007; Sharda et al., 2019). Finally, households that have a nuclear family structure (multiple adults with at least one child) are less likely to score high on the transit-oriented lifestyle, which is consistent with the notion that transit is not very conducive to meeting the complex mobility needs of households with children.

5.2. Bivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the bivariate model of behavioral outcomes. The key finding is that, after controlling for socio-economic, demographic, and attitudinal effects in a joint behavioral modeling framework, ridehailing usage has a statistically significant negative impact on bus use. An increasing frequency of ridehailing usage has the effect of decreasing level of bus use. Similar ridehailing effects on bus ridership and transit usage were observed in Chicago by Soria et al. (2024). Although there have been efforts to leverage ridehailing to complement and enhance transit usage (Shaheen and Cohen, 2020), the results of this study unequivocally show that ridehailing is taking ridership away from bus service – particularly in automobile-oriented metropolitan areas that are generally characterized by dispersed land use patterns and relatively poor transit service (note that this effect of ridehailing usage frequency on bus use may be considered as a “true” causal effect, after accommodating the spurious unobserved correlation between the two endogenous variables engendered by the stochastic latent constructs).

All other effects are as expected and consistent with previous findings in the literature. Pro-environment attitude is associated with lower levels of ridehailing use, a positive perception of mobility services is associated with an inclination towards a higher level of ridehailing use and a decreased level of bus use (similar to results reported by Alyavina et al., 2024), and a transit oriented lifestyle is associated with higher levels of ridehailing and increased bus use (suggesting transit oriented individuals use ridehailing to complement transit as opposed to substitution). These findings are similar to those reported in the literature (Rayle et al., 2016; Dong, 2020; von Behren et al., 2021).

Socio-economic and demographic characteristics significantly influence ridehailing use frequency and change in bus usage arising from the use of ridehailing services. Consistent with prior research, those over the age of 65 years are more likely to use ridehailing services sparingly when compared to younger age groups (Rayle et al., 2016; Alemi et al., 2018). The positive coefficient for the 31-65 years group suggests that frequent ridehailing users in this group are more likely to use ridehailing to complement transit than other age groups.

TABLE 3 Estimation Results of the Joint Ridehailing Use and Bus Use Change Model (N = 1,336)

Explanatory Variables (base category)	Main Outcome Variables			
	Ridehailing Use (rarely, monthly, weekly)		Bus Use Change (decrease, no change, increase)	
	Coef	t-stat	Coef	t-stat
Endogenous variable				
Ridehailing use frequency	—	—	-0.17	-10.59
Latent constructs				
Pro-environment attitude	-0.25	-6.36	—	—
Mobility services perception	0.07	1.29	-0.32	-9.25
Transit-oriented lifestyle	0.46	9.57	0.42	10.99
Individual characteristics				
<i>Age (*)</i>				
31-65 years	—	—	0.25	7.78
Over 65 years	-0.75	-14.85	—	—
<i>Race (White)</i>				
Non-White	-0.07	-1.57	—	—
<i>Employment (not a student)</i>				
Student	—	—	0.22	7.46
Household characteristics				
<i>Household income (*)</i>				
\$50,000 to \$100,000	—	—	0.22	7.22
\$150,000 or more	0.49	14.50	—	—
<i>Household size (*)</i>				
One	0.22	7.52	—	—
Three or more	—	—	0.20	7.37
<i>Household vehicles (zero or at least two)</i>				
One	—	—	-0.14	-5.26
Travel & built environment characteristics				
<i>Weekly VMT (up to 75 & over 100 mi)</i>				
76 to 100 mi	—	—	-0.31	-7.40
<i>Population density (≥ 3,000 person/sq mile)</i>				
Low density (< 3,000 person/sq mile)	-0.25	-10.51	—	—
<i>Location (Austin, Phoenix, Tampa)</i>				
Atlanta	0.15	5.59	—	—
Thresholds				
1 2	0.44	15.13	-1.08	-26.59
2 3	1.59	45.32	1.69	35.81
Correlation				
Ridehailing use	—	—	0.03	—
Data Fit Measures	Joint (GHDM) Model		Independent (IOP) Model	
Log-likelihood at convergence	-1838.49		-1850.23	
Log-likelihood at constants	-1925.09			
Number of parameters	82		32	
Likelihood ratio test	0.045		0.039	
Average probability of correct prediction	0.361		0.359	

Note: Base categories for attributes (*) are identified by the excluded categories.

There is a modest race effect with non-whites likely to use ridehailing services on a less frequent basis. This finding is somewhat contradictory to findings reported in the literature where it has been found that minority groups use ride-hailing services to a greater degree than Whites,

even after controlling for income (Clewlow and Mishra, 2017; Deka and Fei, 2019). It should be noted that this data set is derived from four automobile-oriented sprawled metropolitan regions; as such, some findings may not be perfectly comparable to those reported in the literature as many prior studies have been undertaken in denser and more transit-rich metropolitan areas. In a sprawled region, non-whites are likely to find it challenging to use mobility services on a frequent basis due to poor transit services (hence limited opportunities to use mobility services as first-mile/last-mile connectors) and higher costs associated with the need to traverse longer distances. Students on the other hand are likely to use ridehailing services to connect with transit; they report a higher level of transit use after using ridehailing services.

A higher income is associated with a higher frequency of ridehailing use, a finding that mirrors the literature (e.g., Lavieri and Bhat, 2019; Dong, 2020). The middle-income group appears to show a tendency to increase bus use after ridehailing adoption. This is because they are able to use the service to connect to transit, particularly for commuting; ridehailing services are likely to be cost-effective as a first-mile/last-mile connector, but cost-prohibitive to undertake the entire commute journey by ridehailing. Individuals living alone show a greater inclination to use ridehailing services more frequently, while those in larger households show a propensity to increase bus use after ridehailing adoption. The former finding is consistent with that reported by Sikder (2019), and the latter finding reflects the fact that not all individuals in larger households have access to an automobile and are now able to leverage ridehailing services to complement and elevate their bus use.

In one-vehicle households (which are generally vehicle-deficient households where one or more household members often depend on bus service to meet mobility needs), the greater use of ridehailing services is associated with a propensity to reduce bus use. Individuals in these households have clearly substituted the use of bus transit with ridehailing service. The amount of weekly travel influences bus use change. Those who have a large travel footprint (76-100 miles per week) depict a tendency to reduce bus use and substitute bus use with ridehailing services. In the four metro regions covered by this survey sample, meeting such extensive mobility needs using bus service is challenging, and hence ridehailing services are a superior alternative (thus leading to a tendency to reduce bus use). Lower density living is associated with a higher probability of using ridehailing services less frequently; those in low density neighborhoods are likely to own cars and would find regular use of ridehailing cost prohibitive due to distances that need to be traversed. Respondents from Atlanta report a tendency to use ridehailing services more frequently, presumably due to high density pockets, severe traffic congestion, and opportunities to connect to major transit (e.g., MARTA rail lines). The error correlation across the dependent variables of interest is very small, suggesting that the inclusion of the direct effect of ridehailing use frequency on bus use change captures the relationship between them quite effectively. Consequently, the remaining error correlation that would arise from the presence of correlated unobserved attributes that affect both endogenous variables is modest.

From a goodness-of-fit standpoint, the joint model is found to offer significantly better fit than a corresponding independent model system in which error correlations engendered through the endogenous treatment of latent attitudinal constructs are ignored (restricted to zero by virtue of treating attitudinal variables as exogenous variables, similar to socio-economic and demographic variables). This shows that modeling latent attitudinal constructs and behavioral outcomes of interest in an integrated framework that recognizes endogeneity is critical to capturing the jointness in attitudes and behaviors.

5.3. Average Treatment Effects

The results presented in the previous section can be used to compute the treatment effects of specific explanatory variables on the main outcome variables of interest. This is important because the total effect of a variable on an endogenous variable of interest may comprise both a direct effect as well as any indirect effects engendered through latent constructs. This section is devoted to presenting average treatment effects (ATEs) for different variables with a view to shed additional insights on the influence of different factors in shaping the endogenous variables of interest.

When translating the estimated model coefficients into actual treatment effects, it should be noted that the magnitude of the effects will vary across individuals due to the non-linear nature of the model specification. To account for this, average effects are estimated by calculating the mean of the effect of a variable across all individuals in the sample. Average treatment effects (ATEs) can then be determined by computing the difference in mean outcomes between those assigned to the treatment group and those assigned to the control (base) group for each explanatory variable. In the context of the modeling framework adopted in this study, ATEs show the impact on a downstream posterior variable of interest due to a treatment that alters an antecedent variable from one state to another. For instance, if the goal is to determine the effect of population density on the frequency of ridehailing use, one state corresponds to individuals residing in low-density areas, and a different state is one where individuals reside in high-density areas. The impact of this change in state is represented by the change in expected ridehailing use frequency. Additionally, if an exogenous variable influences the outcome variables through one or more mediating latent constructs, then the coefficient estimates associated with this (exogenous) variable can be used to partition out the corresponding ATE into its subeffects in percentage terms. Further information about the calculation of ATEs, including mathematical formulations, can be found elsewhere (Bhat and Eluru, 2009; Blazanin et al., 2022).

For ease of interpretation, the two main outcome variables (ridehailing use frequency and bus use change) are transformed into binary variables before computing the average treatment effects. The binary categories for ridehailing use are weekly and non-weekly; and for bus use change, the categories correspond to an increase in bus use and no increase in bus use. With this transformation, the ATE values are calculated and presented in Table 4. For ease of presentation, only two extreme categories are considered in each of the exogenous variables. The ATE values, including direct and indirect effects through latent constructs, are shown in the table. It is important to recognize that the ATE values are quite modest due to the small numbers of individuals in the sample who are weekly ridehailing users and who increased their bus use. To provide a clearer interpretation of these values, Table 4 also presents the percent average treatment effects (PATEs). These PATEs indicate the relative magnitude of change in the outcome variables due to the treatment, relative to the base group.

TABLE 4 Average Treatment Effects (ATEs) for Ridehailing Use and Bus Use Change (N = 1,336)

Variable	Base level	Treatment	Contribution through latent constructs or direct effect (%)				ATE	PATE (%)
			PEA	MSP	TOL	Direct effect		
Ridehailing Use: Weekly								
<i>Individual characteristics</i>								
Age	18-30 years	Over 65 years	4.2	5.0	0.0	90.8	-0.0723	-80.3
Education	High school or less	Graduate degree(s)	34.5	0.0	65.5	0.0	-0.0099	-39.2
Race	White	Non-White	0.0	39.8	0.0	60.2	-0.0008	-5.1
Employment	Not a student	Student	100.0	0.0	0.0	0.0	-0.0032	-20.2
<i>Household and built environment characteristics</i>								
Household income	Up to \$50,000	\$100,000 or over	0.0	6.2	30.0	63.8	0.0072	94.9
Household size	One	Three or more	0.0	0.0	0.0	100.0	-0.0072	-39.8
Household structure	Not a nuclear family	Nuclear family	0.0	0.0	100.0	0.0	-0.0041	-34.4
Population density	≥ 3,000 person/mi ²	< 3,000 person/mi ²)	0.0	0.0	0.0	100.0	-0.0046	-45.0
Location	Not Atlanta	Atlanta	0.0	0.0	0.0	100.0	0.00210	43.7
Bus Use Change: Increase								
<i>Endogenous variable</i>								
Ridehailing Use	Rarely	Weekly	0.0	0.0	0.0	100.0	-0.0267	-84.8
<i>Individual characteristics</i>								
Age	18-40 years	Over 65 years	0.0	100.0	0.0	0.0	0.0185	63.7
Education	High school or less	Graduate degree(s)	0.0	0.0	100.0	0.0	-0.0127	-21.4
Race	White	Non-White	0.0	100.0	0.0	0.0	-0.0183	-34.6
Employment	Not a student	Student	0.0	0.0	0.0	100.0	0.0175	59.7
<i>Household, travel, and built environment characteristics</i>								
Household income	Up to \$50,000	\$100,000 or over	0.0	50.9	49.1	0.0	0.0001	0.6
Household size	One	Three or more	0.0	0.0	0.0	100.0	0.0194	49.8
Household structure	Not a nuclear family	Nuclear family	0.0	0.0	100.0	0.0	-0.0164	-26.4
Household vehicles	Zero or at least two	One	0.0	0.0	0.0	100.0	-0.0124	-25.2
Weekly VMT	up to 75 & over 100 mi	76 to 100 mi	0.0	0.0	0.0	100.0	-0.0190	-49.1

A brief explanation of the ATEs presented in Table 4 is as follows. The impact of age on ridehailing frequency as measured by its ATE is -0.0723. This means that if 100 individuals aged 18 to 30 were replaced by 100 individuals aged 65 or older, the sample would have seven fewer instances of weekly ridehailing users. While this number may seem small, the PATE (percent ATE) for this corresponding ATE is -80.3 percent, indicating that the number of weekly ridehailing users decreased by 80.3 percent with this shift in age groups. When breaking down the ATE value into its subeffects, it is found that 9.2 percent of the ATE is an indirect effect, with 4.2 percent of the indirect effect coming from *pro-environment attitude* and five percent coming from positive *mobility services perception*. The remaining 90.8 percent is a direct effect. On the contrary, the effect of age on bus use change as measured by its PATE is 63.7 percent (when the same treatment is applied). This is entirely an indirect effect engendered by positive *mobility services perception*. This result indicates that if 100 individuals within the age range of 18 to 40 were replaced by 100 individuals aged 65 or over, there would be a 63.7 percent increase in the number of people who elevated their bus use after adopting ridehailing services. This finding is consistent with expectations. Although younger individuals may be more inclined to use ridehailing services, they may be more inclined to do so in a transit substitution mode. Older individuals who are likely to be more mobility challenged and income constrained may be more inclined to use transit services if they had good first mile/last mile connectivity. Ridehailing services could fulfill transit connectivity needs, thus enabling older individuals to increase their reliance on bus services for mobility. Older individuals may benefit from policies and programs that focus on providing information about the use of ridehailing services to connect to transit, integrated fare payment systems, and incentives (subsidies) for using ridehailing services as a means of getting to/from bus stops.

Being a student has a negative indirect effect on ridehailing use through the latent construct, *pro-environment attitude*, as shown by a PATE value of -20.2 percent. Targeting students for environmental awareness campaigns may help reduce use of ridehailing services. Conversely, being a student has a positive direct impact on bus use change, with a PATE value of 59.7 percent. Students tend to be more environmentally conscious and often rely on transit for their daily travel needs, and are therefore likely to increase bus use after the adoption of ridehailing services as such services serve as first mile/last mile connectors. Household size also has a direct impact on ridehailing use and bus use change, with single-person households using ridehailing more often than larger households (three or more persons) as evidenced by the PATE value of -39.8. On the other hand, persons in larger households are more likely to have increased their bus use after adopting ridehailing services as evidenced by the PATE value of 49.8 percent. Larger households are found to reside in lower density areas necessitating travel across greater distances to accomplish activities. Persons in these households are therefore more inclined to use ridehailing services in a manner that complements transit (than residents in single-person households).

In terms of the effect of ridehailing use itself, switching from the category of rarely using ridehailing service to the category of using ridehailing service on a weekly basis is associated with a PATE value of -84.8 percent. This is a strong indicator that ridehailing serves more as a substitute for transit than as a complement to transit. To mitigate the substitution effects of ridehailing on transit, policies and programs that discourage frequent use of ridehailing should be put in place. Targeted incentives/subsidies that help integrate ridehailing services with bus service in a very affordable way would help promote ridehailing service use in a complementary modality. Overall, the ATE computations help in drawing robust inferences regarding effects of different variables, and identifying potential strategies that can mitigate unintended and undesirable outcomes.

6. STUDY IMPLICATIONS AND CONCLUSIONS

This study focuses on the interaction between ridehailing service usage and change in bus use that results from the use of ridehailing services. The paper utilizes a data set comprising respondents from the metro regions of Phoenix, Atlanta, Austin, and Tampa. The survey specifically asked individuals to convey their attitudes toward ridehailing services, the frequency with which they used ridehailing services, and the extent to which their bus use has changed due to ridehailing usage. In order to better understand and isolate the effect of ridehailing services on bus use change, this paper adopts a simultaneous equations modeling framework in which joint relationships among multiple endogenous variables are captured explicitly. The model system accounts for the influence of latent attitudinal factors and treats them as endogenous variables as well.

The findings of this study clearly show that ridehailing usage negatively impacts bus use. Descriptive statistics as well as model estimation results indicate that ridehailing use frequency is significantly associated with a decrease in bus use, suggesting that ridehailing serves as a transit substitute (more than it serves as a complement). Despite attempts to have ridehailing services provide first-mile/last-mile connectivity and serve as a complement to transit, this has not happened for the most part – at least in auto-oriented metropolitan regions with dispersed land use patterns and rather limited transit service. After accounting for a host of socio-economic, demographic, and attitudinal factors, the effect of ridehailing is that it takes away from bus ridership.

The results are not surprising. Ridehailing is convenient, flexible, agile, faster (than transit), and personalized – these are many of the traits that render a mode appealing. It is more expensive, but also regarded superior to traditional taxi and unlikely to be cost-prohibitive for short trips of a few miles (more than 60 percent of daily trips in the United States are five miles or less). Ridehailing also removes the hassle of driving and parking. It is clear why ridehailing is highly competitive and able to take trips away from public transit. As shared on-demand mobility services that are electrified and automated increasingly make their way into the transportation landscape, the future of transit is under threat – and the threat has been exacerbated by the pandemic and the new remote modalities and realities of work, school, shopping, dining, and recreation embraced by the public. Transit ridership was already on the decline prior to the pandemic, and this analysis suggests that the rise of ridehailing services played a key role in contributing to the decline (the survey data pertains exclusively to the pre-pandemic period).

To reverse the transit decline, municipalities and transit agencies need to explore strategies to enhance service and ridership, particularly in auto-oriented regions that have dispersed land use patterns. Partnering with ridehailing services so that first-mile/last-mile connectivity to transit is enhanced, fare payment systems are integrated, and the cost of ridehailing access/egress segments is highly subsidized would help transit agencies utilize emerging mobility services more effectively to boost ridership, as noted by Ziedan et al. (2024) and Boarnet et al. (2024). Transit agencies themselves could reconfigure their service to expand coverage and enhance connectivity and accessibility with a focus on key travel corridors, market segments, and destinations. Recent attempts at reconfiguring services have worked to increase ridership in a few areas; examples include the Houston and Seattle metro areas (Descant, 2018) and the Northern Kentucky area (Tindale-Oliver, 2021). In all of these regions, transit services were expanded, routes were redrawn to bring about more direct connections and enhance both speed and reliability, access to destinations and people with mobility limitations was improved, and public input was considered throughout the process of reconfiguration.

Municipalities may need to consider charging an additional fee on ridehailing services and use the revenue obtained to enhance transit services and mobility options for residents. Ridehailing services have already shown to increase congestion (Diao et al., 2021) and this study shows that they take ridership away from transit too. The levying of a fee would help manage the demand for ridehailing services while providing additional revenue for enhancing transit services and access for disadvantaged groups. Transit agencies will be in a better position to provide customized mobility, similar to the RideChoice program currently offered by Valley Metro in the Greater Phoenix region for transportation disadvantaged groups (Valley Metro, 2024). Concerted efforts aimed at increasing awareness about transit options, influencing attitudes and values, and changing perceptions may further help stem the loss of transit ridership. Since those with pro-environmental attitudes are found to be less inclined to use ridehailing services, marketing campaigns that bring about greater environmental awareness may be helpful.

The future of transit remains uncertain. Transit agencies are beginning to experiment with novel approaches to enhancing service, including fare free service, flexible shared on-demand van services, and greater presence of security personnel. These strategies need to be pursued with the level of investment and intensity necessary to bring about meaningful change. In the absence of significant investments in service, safety, and technology, partnerships with new and emerging mobility providers, and enhancements in service configuration that boost accessibility, it is likely that transit will continue to experience a downward spiral – at least in part due to the rise of ridehailing services.

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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, S. Khoeini, T.B. Magassy, R.M. Pendyala, C.R. Bhat; analysis and interpretation of results: I. Batur, K.E. Asmussen, A. Mondal, R.M. Pendyala, C.R. Bhat; draft manuscript preparation: I. Batur, K.E. Asmussen, A. Mondal, T.B. Magassy, R.M. Pendyala, C.R. Bhat. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

- Acheampong, R. A., A. Siiba, D. K. Okyere, and J. P. Tuffour. Mobility-on-demand: An empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. *Transportation Research Part C*, 2020. 115:102638.
- Alemi, F., G. Circella, S. Handy, and P. Mokhtarian. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society*, 2018. 13:88–104.
- Alyavina, E., A. Nikitas, and E. T. Njoya. Mobility-as-a-service and unsustainable travel behaviour: Exploring MaaS’car ownership and public transport trip replacement side-effects. *Transport Policy*, 2024.

- APTA. Transit and TNC partnerships. *American Public Transportation Association*, 2020. <https://www.apta.com/research-technical-resources/mobility-innovation-hub/transit-and-tnc-partnerships/>. Accessed May 1, 2024.
- Atkinson-Palombo, C., L. Varone, and N. W. Garrick. Understanding the surprising and oversized use of ridesourcing services in poor neighborhoods in New York City. *Transportation Research Record*, 2019. 2673:185–194.
- Bansal, P., A. Sinha, R. Dua, and R. A. Daziano. Eliciting preferences of TNC users and drivers: Evidence from the United States. *Travel Behaviour and Society*, 2020. 20:225–236.
- Bhat, C. R. A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B*, 2015. 79:50–77.
- Bhat, C. R. New matrix-based methods for the analytic evaluation of the multivariate cumulative normal distribution function. *Transportation Research Part B*, 2018. 109:238–256.
- Bhat, C. R. and N. Eluru. A copula-based approach to accommodate residential self-selection effects in travel behavior modeling. *Transportation Research Part B*, 2009. 43:749–765.
- Bi, H., Z. Ye, L. Hu, and H. Zhu. Why they don't choose bus service? Understanding special online car-hailing behavior near bus stops. *Transport Policy*, 2021. 114:280–297.
- Blazanin, G., A. Mondal, K.E. Asmussen, and C. R. Bhat. E-scooter sharing and bikesharing systems: an individual-level analysis of factors affecting first use and use frequency. *Transportation Research Part C*, 2022. 135:103515.
- Boarnet, M. G., Q. Shao, and C. A. Pilgram. Monetary cost, time cost, and mode choice: transit and ridehailing in California. *Transportation Research Part D: Transport and Environment*, 2024. 130:104149.
- Boisjoly, G., E. Grisé, M. Maguire, M.-P. Veillette, R. Deboosere, E. Berrebi, and A. El-Geneidy. Invest in the ride: a 14 year longitudinal analysis of the determinants of public transport ridership in 25 North American cities. *Transportation Research Part A*, 2018. 116:434–445.
- Cervero, R. Transit-oriented development's ridership bonus: a product of self-selection and public policies. *Environment and Planning A*, 2007. 39:2068–2085.
- Chakraborty, A., and S. Mishra. Land use and transit ridership connections: implications for state-level planning agencies. *Land Use Policy*, 2013. 30:458–469.
- Circella, G., F. Alemi, K. Tiedeman, S. Handy, and P. L. Mokhtarian. The adoption of shared mobility in California and its relationship with other components of travel behavior. *UC Davis: National Center for Sustainable Transportation*, 2018. <https://escholarship.org/uc/item/1kq5d07p>. Accessed May 1, 2024.
- Clewlow, R. R. and G. S. Mishra. Disruptive transportation: the adoption, utilization, and impacts of ride-hailing in the United States. *Research Report, UC Davis Institute of Transportation Studies*. 2017.
- Deka, D., and D. Fei. A comparison of the personal and neighborhood characteristics associated with ridesourcing, transit use, and driving with NHTS Data. *Journal of Transport Geography*, 2019. 76:24–33.
- Descant, S. Seattle, Houston buck declining bus ridership trend. *Government Technology*, 2018. <https://www.govtech.com/fs/transportation/seattle-houston-buck-declining-bus-ridership-trend.html>. Accessed May 1, 2024.
- Diab, E., D. Kasraian, E. J. Miller, and A. Shalaby. The rise and fall of transit ridership across Canada: Understanding the determinants. *Transport Policy*, 2020. 96:101–112.
- Diao, M., H. Kong, and J. Zhao. Impacts of transportation network companies on urban mobility. *Nature Sustainability*, 2021. 4:494–500.

- Dong, X. Trade Uber for the bus? An investigation of individual willingness to use ride-hail versus transit. *Journal of the American Planning Association*, 2020. 86:222–235.
- Dong, X., E. Guerra, and R. A. Daziano. Impact of TNC on travel behavior and mode choice: a comparative analysis of Boston and Philadelphia. *Transportation*, 2021.
- Gehrke, S. R., A. Felix, and T. G. Reardon. Substitution of ride-hailing services for more sustainable travel options in the Greater Boston region. *Transportation Research Record*, 2019. 2673:438–446.
- Ghaffar, A., S. Mitra, and M. Hyland. Modeling determinants of ridesourcing usage: A census tract-level analysis of Chicago. *Transportation Research Part C*, 2020. 119:102769.
- Gomez, J., Á. Aguilera-García, F. F. Dias, C. R. Bhat, and J. M. Vassallo. Adoption and frequency of use of ride-hailing services in a European city: The case of Madrid. *Transportation Research Part C*, 2021. 131:103359.
- Graehler, M., R. A. Mucci, and G. D. Erhardt. Understanding the recent transit ridership decline in major US cities: Service cuts or emerging modes? Presented at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C., 2019.
- Hall, J. D., C. Palsson, and J. Price. Is Uber a substitute or complement for public transit? *Journal of Urban Economics*, 2018. 108:36–50.
- Henao, A., and W. E. Marshall. The impact of ride-hailing on vehicle miles traveled. *Transportation*, 2018. 46:2173–2194.
- Kang, S., A. Mondal, A. C. Bhat, and C. R. Bhat. Pooled versus private ride-hailing: a joint revealed and stated preference analysis recognizing psycho-social factors. *Transportation Research Part C*, 2021. 124:102906.
- Khoeini, S., R. M. Pendyala, D. Salon, G. Circella, P. L. Mokhtarian, C. R. Bhat, M. Maness, N. Mennon, D. Capasso da Silva, I. Batur, F. Dias, S. Kang, and Y. Lee. TOMNET Transformative Transportation Technologies (T4) Survey. <https://tomnet-utc.engineering.asu.edu/data/t4-survey/>. Accessed May 1, 2024.
- Lavieri, P. S., and C. R. Bhat. Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part C*, 2019. 105:100–125.
- Lavieri, P. S., F. F. Dias, N. R. Juri, J. Kuhr, and C. R. Bhat. A model of ridesourcing demand generation and distribution. *Transportation Research Record*, 2018. 2672:31–40.
- Li, W., A. Shalaby, and K. N. Habib. Exploring the correlation between ride-hailing and multimodal transit ridership in Toronto. *Transportation*, 2021. 49:765–789.
- Liao, Y. Ride-sourcing compared to its public-transit alternative using big trip data. *Journal of Transport Geography*, 2021. 95:103135.
- Loa, P., S. M. Mashrur, and K. Nurul Habib. What influences the substitution of ride-sourcing for public transit and taxi services in Toronto? An exploratory structural equation model-based study. *International Journal of Sustainable Transportation*, 2021. 17(1):1–14.
- McCarthy, L., A. Delbosc, G. Currie, and A. Molloy. Factors influencing travel mode choice among families with young children (aged 0–4): A review of the literature. *Transport Reviews*, 2017. 37:767–781.
- Ngo, N. S., T. Götschi, and B. Y. Clark. The effects of ride-hailing services on bus ridership in a medium-sized urban area using micro-level data: Evidence from the Lane Transit District. *Transport Policy*, 2021. 105:44–53.

- Rayle, L., D. Dai, N. Chan, R. Cervero, and S. Shaheen. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy*, 2016. 45:168–178.
- Shaheen, S. and A. Cohen. Mobility on Demand (MOD) and Mobility as a Service (MaaS): Early understanding of shared mobility impacts and public transit partnerships. In C. Antoniou, D. Efthymiou, and E. Chaniotakis (eds.) *Demand for Emerging Transportation Systems*, 2020. 37–59.
- Sharda, S., S. Astroza, S. Khoeini, I. Batur, R. M. Pendyala, and C. R. Bhat. Do attitudes affect behavioral choices or vice-versa: uncovering latent segments within a population. Presented at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C., 2019.
- Sikder, S. Who uses ride-hailing services in the United States? *Transportation Research Record*, 2019. 2673:40–54.
- Soria, J., D. Edward, and A. Stathopoulos. Requiem for transit ridership? An examination of who abandoned, who will return, and who will ride more with mobility as a service. *Transport Policy*, 2023. 134:139-154.
- Taylor, B. D., D. Miller, H. Iseki, and C. Fink. Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas. *Transportation Research Part A*, 2009. 43:60–77.
- Tindale-Oliver, Inc. TANK Transit Network Study. 2021. https://spark.adobe.com/page/ZP4ZQ39Nd5fUD/?mc_cid=5a9c08916a&mc_eid=c4822fae1f. Accessed May 1, 2024.
- Tirachini, A. Ride-hailing, travel behaviour and sustainable mobility: An international review. *Transportation*, 2019. 47:2011–2047.
- Tirachini, A. and M. del Río. Ride-hailing in Santiago de Chile: Users’ characterisation and effects on travel behaviour. *Transport Policy*, 2019. 82:46–57.
- Valley Metro. RideChoice. 2024. <https://www.valleymetro.org/accessibility/ridechoice>. Accessed May 1, 2024.
- Vinayak, P., F. F. Dias, S. Astroza, C. R. Bhat, R. M. Pendyala, and V. M. Garikapati. Accounting for multi-dimensional dependencies among decision-makers within a generalized model framework: An application to understanding shared mobility service usage levels. *Transport Policy*, 2018. 72:129–137.
- von Behren, S., B. Chlond, and P. Vortisch. Exploring the role of individuals’ attitudes in the use of on-demand mobility services for commuting – A case study in eight Chinese cities. *International Journal of Transportation Science and Technology*, 2022. 11(2):229-242.
- Wiernik, B. M., D. S. Ones, and S. Dilchert. Age and environmental sustainability: A meta-analysis. *PsycEXTRA Dataset*, 2011.
- Woodall, B. U.S. auto sales in 2015 set record after strong December. *Reuters*, 2016. <https://www.reuters.com/article/us-usa-autos/u-s-auto-sales-in-2015-set-record-after-strong-december-idUSKBN0UJ1C620160105>. Accessed May 1, 2024.
- Young, M., and S. Farber. The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. *Transportation Research Part A*, 2019. 119:383–392.
- Ziedan, A., A. Hightower, L. Lima, and C. Brakewood. The app or the cap? Which fare innovation affects bus ridership? *Transport Policy*, 2024. 145:247-258.