Final Project Report

Evolution of Mode Use Due to COVID-19 Pandemic in the United States: Implications for the Future of Transit

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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The COVID-19 pandemic has brought about transformative changes in human activity-travel patterns. These lifestyle changes were naturally accompanied by and associated with changes in transportation mode use and work modalities. In the United States, most transit agencies are still grappling with lower ridership levels, thus signifying the onset of a new normal for the future of transit. This report addresses this challenge using a novel panel survey data set collected for a representative sample of individuals from across the United States. The study involved the estimation of a panel multinomial probit model of mode choice to capture both socio-economic effects and period (pre-, during-, and post-COVID) effects that contribute to changes in mode choice. This work provides rich insights into the evolution of commute mode use as a result of the pandemic, with a particular focus on public transit. Through a rigorous modeling approach, this study provides a deep understanding of how transit use has evolved, how it is likely to evolve into the future, and the socio-economic and demographic characteristics that affect the evolution of (and expected future use of) public transit. Results suggest that transit patronage is likely to remain depressed by about 30 percent for the foreseeable future, in the absence of substantial changes in service configurations. This study also shows that minority groups and those living in higher density regions are more likely to exhibit transit use recovery in the post-pandemic period.</td></tr>
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EXECUTIVE SUMMARY

The COVID-19 pandemic has brought about transformative changes in human activity-travel patterns. These lifestyle changes were naturally accompanied by and associated with changes in transportation mode use and work modalities. In the United States, most transit agencies are still grappling with lower ridership levels, thus signifying the onset of a new normal for the future of transit. This report addresses this challenge using a novel panel survey data set collected for a representative sample of individuals from across the United States. The study involved the estimation of a panel multinomial probit model of mode choice to capture both socio-economic effects and period (pre-, during-, and post-COVID) effects that contribute to changes in mode choice. This work provides rich insights into the evolution of commute mode use as a result of the pandemic, with a particular focus on public transit. Through a rigorous modeling approach, this study provides a deep understanding of how transit use has evolved, how it is likely to evolve into the future, and the socio-economic and demographic characteristics that affect the evolution of (and expected future use of) public transit. Results suggest that transit patronage is likely to remain depressed by about 30 percent for the foreseeable future, in the absence of substantial changes in service configurations. This study also shows that minority groups and those living in higher density regions are more likely to exhibit transit use recovery in the post-pandemic period.

INTRODUCTION

Over the past two years, the COVID-19 pandemic has brought about transformative changes in mobility, human activity-travel patterns, mode use, work modalities, and means of interaction (Tirachini and Cats, 2020; Matson et al., 2021; De Vos, 2020). Concerns about public health and welfare, and the potential harmful effects of virus spread, motivated many jurisdictions to implement lockdowns, stay-at-home mandates, and business closures. Employers quickly transitioned their employees (wherever possible) to work-from-home (WFH), educational institutions pivoted to remote learning modalities, stores and restaurants offered options to order goods and services online and have them delivered or available for contactless pickup, thus enabling a drastic reduction in the need to travel and engage in face-to-face interactions (Wang et al., 2021; Shamshiripour et al., 2020).

As a result of these changes, society experienced very significant changes across all aspects of life. The amount of travel undertaken for commute and non-commute purposes dropped significantly during the pandemic (Javadinasr et al., 2021; Park et al., 2022; Mohammadi et al., 2022). With the ability to work, learn, shop and order food, and conduct business from home, individuals engaged in less travel and activity engagement outside home. These lifestyle changes were naturally accompanied by and associated with changes in transportation mode use. In particular, transit use dropped dramatically, partly due to public health concerns related to using shared modes of mobility and partly due to the reduced need for many to use transit in the wake of greater levels of home-based work and virtual activity engagement (Liu et al., 2020; Javadinasr et al., 2021). Many transit agencies have experienced substantial reductions in transit ridership, and the recovery of transit ridership, even as the pandemic has waned in 2022, has been slow and tepid. In the United States, most transit agencies have not even recovered one-half of the pre-pandemic ridership levels, thus signifying the onset of a new normal for the future of transit (Salon et al., 2021; Liu et al., 2020)

Transit agencies are grappling with the implications of substantial drops in ridership and associated fare revenue, and are being forced into changing service levels (e.g., frequency) and service coverage (both spatially and temporally). These reductions in service levels are further exacerbating the situation as people find it impractical to use transit to meet their mobility needs and increasingly choose to use mobility-as-a-service (MaaS) or other modes to travel (Brown and Williams, 2021; Bhaduri et al., 2020). Transit was already experiencing a slow decline in ridership in the pre-pandemic era due to a healthy economy (that facilitated high levels of car ownership), affordable fuel prices, and widespread availability of mobility-on-demand services that offered very flexible and convenient transportation. The pandemic has greatly accelerated the reduction in transit use and the transition to other modes of transportation that are perceived as safer (both from a health and a crime standpoint) and more convenient. With employers and employees increasingly embracing work-from-home and hybrid work modalities, hopes for a rapid and full recovery of transit ridership are increasingly fading (Vickerman, 2021).

Transit is, however, a very important mode of transportation that serves as a critical lifeline for many individuals. Transit serves the mobility needs of minorities, low-income individuals, individuals unable to own or operate a private vehicle, individuals with mobility limitations, and workers who must travel to service-oriented jobs. If transit services were to decline, many of these individuals may find it difficult to meet their commute and travel needs, especially because mobility-on-demand services (such as ridehailing services) continue to be prohibitively expensive for daily/frequent use. Thus the future of transit is of great concern for transportation planners, policymakers, businesses, and individuals who have come to rely on transit for meeting mobility needs.

It is therefore imperative to understand the evolution of transportation mode usage over the course of the pandemic and (expected) into the future, with a particular focus on transit use. Through such an analysis, it will be possible to understand the factors contributing to the drop in transit use, what transit users of the past (pre-COVID) are doing in the COVID era, and the degree to which transit use may or may not recover in the post-COVID era. In order to shed light on this evolutionary phenomenon, this study uses a unique panel data set derived from the COVID Future Survey study (Chauhan et al., 2021). This nationwide survey in the United States provides very rich longitudinal data on the activity, travel, and mode use patterns of a large sample of individuals. The data provides information on what individuals did prior to and during the pandemic, and what they *expect* to do after the pandemic is no longer a threat (with respect to activity engagement, activity modality, and mode use).

The study employs a novel modeling approach to understand and quantify the evolution of transit use. The model considers *three* time periods: before, during, and after (expected) the pandemic is considered no longer a threat. Because of the panel nature of the data set (where information is available for the same individual at three points in time), it is possible to determine the COVID effect on transit use, and separate this effect from other pure exogenous variable effects (such as those stemming from socio-economic and demographic variables). A set of exogenous variables including socio-economic and demographic attributes, built environment attributes, health concerns and perceptions of the virus, and work/occupation characteristics are included in the model. The model is a simple multinomial discrete choice model, but incorporates appropriate time period indicators so that COVID shift effects can be explicitly represented and estimated. Through the consideration of three different time points (pre-pandemic, during the height of the pandemic, and expected post-pandemic), the study is able to show the extent to which COVID contributed to the fall in transit ridership during the height of the pandemic as well as the extent to which transit ridership is *expected* to recover following the pandemic. In addition, the model includes a series of latent attitudinal factors/constructs that capture attitudes, perceptions, and lifestyle preferences, and risk tolerance and risk averseness. Through such a comprehensive model specification, the study aims to unravel the short- and long-term effects of COVID on transit. Armed with such knowledge, it will be possible for transit agencies to formulate effective transit recovery strategies and plan for a longer-term significantly altered future state.

The remainder of this report is organized as follows. The next section presents a detailed description of the data and the endogenous variables of interest. The third section presents the modeling framework and methodology, followed by the fourth section that presents detailed model estimation results. Then, the fifth section depicts the computation of exogenous variable and COVID shift effects. Finally, the sixth section offers a discussion of the study implications and concluding thoughts.

DATA DESCRIPTION

This section presents an overview of the data set used in this study. A description of the survey and a summary of sample socio-economic and demographic characteristics are presented first. This is followed by a detailed description of the endogenous variable of interest (mode choice) and latent attitudinal factors.

The COVID Future Survey and Sample Characteristics

The data set used in this study is derived from the COVID Future Survey, a nationwide panel survey conducted in the United States. The online panel survey gathered detailed information about socio-economic and demographic attributes, travel and mobility choices, attitudes and perceptions, lifestyle and modal preferences, work and education modalities (in-person, virtual, hybrid), activity engagement patterns (including virtual activity engagement), technology use patterns, and mode use for commute and non-commute travel. Participants were recruited via multiple methods to help mitigate any sampling biases that may arise from the use of a single recruitment method. Recruitment methods included the use of an online survey panel, outreach to a large random sample of e-mail addresses purchased from a commercial vendor, and outreach to a convenience sample of contacts and colleagues through social media and personal communications.

The longitudinal panel survey was administered at different time points throughout the pandemic to track changes in activity and mobility choices over time (as external and internal household/personal circumstances changed). The first wave of the survey was conducted soon after the onset of the pandemic in the United States, during the period of April 2020 through October 2020. A total of 9,912 individuals responded to the survey. In addition to providing information about what they were doing (in terms of activity-travel patterns and mode use) during the pandemic, the respondents provided information about their pre-pandemic behaviors and mobility choices. The second wave of the survey was administered to the first-wave respondent sample during November 2020 through May 2021, a period during which vaccinations were rolled out to increasingly larger segments of the population. A total of 3,093 individuals responded to the second wave of the survey. Finally, the third wave of the survey was administered during October-November 2021. By the time the third wave was administered, vaccinations were widely available. A total of 2,860 individuals responded to the third wave of the survey.

The COVID Future Survey yielded a rich longitudinal panel data set for about 2,000 individuals across the United States who responded to all three waves. In each wave of the survey, individuals answered questions about their activities and mobility choices at the time that they were responding to the survey and about what they *expected* to do (in terms of activities and mobility choices) in a post-pandemic era when the COVID-19 virus is no longer a threat. Further details about the COVID Future Survey are available in Chauhan et al. (2021).

The first wave contains mode choice data at the height of the pandemic, thus offering the ability to evaluate the impacts of a severe and prolonged disruption on mode choice (relative to the pre-pandemic era). Even though the second and third waves provide additional data for tracking evolution of mode use, this study is largely concerned with assessing the extent to which transit use will recover in the post-pandemic period. For this reason, the analysis and modeling effort of this study utilizes data corresponding to three time points: *before COVID* (pre-pandemic), *during (the peak of) COVID*, and *post-COVID* (when the pandemic is no longer considered a threat). Data about pre-pandemic choices were collected through a series of retrospective questions included in the first wave survey questionnaire. Wave 1 data offer information about activities and mobility choices during the peak of COVID in 2020. The expected post-pandemic behaviors were asked in every survey wave; the answers provided in the third wave are used in this study as it is likely that people were most confident about their stated behavioral intentions in a post-pandemic era.

The focus of this work is on the evolution of commute mode choice. As such, only workers in the sample of individuals who responded to the first and third waves of the survey were extracted for analysis. After extracting the worker subsample and filtering observations with missing data, the final analysis subsample includes 930 workers. Table 1 presents the subsample characteristics.

Table 1 Sample Socio-economic and Demographic Characteristics

Individual Characteristics (N = 930) Variable	%	**Household Characteristics (N = 930)** Variable	%
Gender		**Household annual income**	
Female	58.9	Less than $25,000	5.2
Male	41.1	$25,000 to $49,999	15.2
Age category		$50,000 to $99,999	37.7
18-30 years	8.3	$100,000 to $149,999	22.5
31-40 years	20.8	$150,000 to $249,999	9.2
41-50 years	21.4	$250,000 or more	10.2
51-60 years	27.4	**Household size**	
61-70 years	18.2	One	17.6
71+ years	4.0	Two	38.0
Employment status		Three or more	44.4
A worker (part-time or full-time)	93.7	**Housing unit type**	
Both a worker and a student	6.3	Stand-alone home	70.9
Education attainment		Condo/apartment	17.8
Completed high school or less	7.2	Other	11.3
Some college or technical school	23.0	**Home ownership**	
Bachelor's degree(s)	38.7	Own	74.1
Completed graduate degree(s)	31.1	Rent	23.2
Race		Other	2.7
Asian or Pacific Islander	6.5	**Vehicle ownership**	
Black or African American	6.0	Zero	4.1
Native American	1.2	One	34.7
White or Caucasian	83.7	Two	43.3
Other	2.7	Three or more	17.8

Commute Mode Before the Pandemic	%	**Commute Mode During the Pandemic**	%	**Commute Mode After (expected) the Pandemic**	%
Private vehicle	74.5	Private vehicle	49.5	Private vehicle	71.8
Transit	9.0	Transit	2.5	Transit	6.7
Work-from-home	12.6	Work-from-home	45.4	Work-from-home	17.3
Other	3.9	Other	2.7	Other	4.2

The sample has a larger share of females. The age distribution shows that larger shares of respondents are in the middle age groups with smaller shares in the extreme age groups. Given that this is an exclusive worker sample, such a distribution is expected. Educational attainment is fairly high with 38.7 percent completing a Bachelor's degree and another 31.1 percent completing graduate or professional degrees. About 84 percent of respondents are White, with six percent Black and 6.5 percent Asian or Pacific Islander. The annual household income distribution shows that only about five percent are in the lowest income bracket of $25,000 or less while about 10 percent fall into the highest income group of $250,000 or more. It is found that 44.4 percent of the respondents reside in households with three or more individuals and 38 percent reside in two-person households. About 71 percent of respondents reside in stand-alone homes, and a similar percentage (74.1 percent) own the home in which they live. Only about four percent of the respondents live in households with no vehicles; 43.3 percent reside in households with two vehicles. Overall, the sample exhibits socio-economic and demographic attribute distributions that are consistent with expectations (for a worker subsample) and appropriate for behavioral modeling.

Endogenous Variables and Attitudinal Factors

The endogenous variable of interest in this study is *commute mode choice.* This information was gathered in slightly different ways in each wave, but there is enough consistency in the question wording and response pattern to provide confidence that the response distributions are comparable over time. The commute mode response options are coded in this study into four key categories: private vehicle (regardless of occupancy), transit (bus and rail), work-from-home, and other (includes bicycle and walk). In each instance, respondents were asked to identify the mode of transportation (including work-from-home) used most often to travel to/from work. For the post-pandemic period, respondents were asked to identify the mode that they *expect* to use most frequently to go to/from work in a post-COVID new normal. The bottom of Table 1 provides the distribution of the endogenous mode choice variable at different time points. The evolution of mode choice over time, shown as a Sankey diagram in Figure 1, suggests that there is a fairly high degree of expectation of returning to the pre-pandemic state in a post-COVID future, although some behavioral changes that happened during COVID are likely to persist.

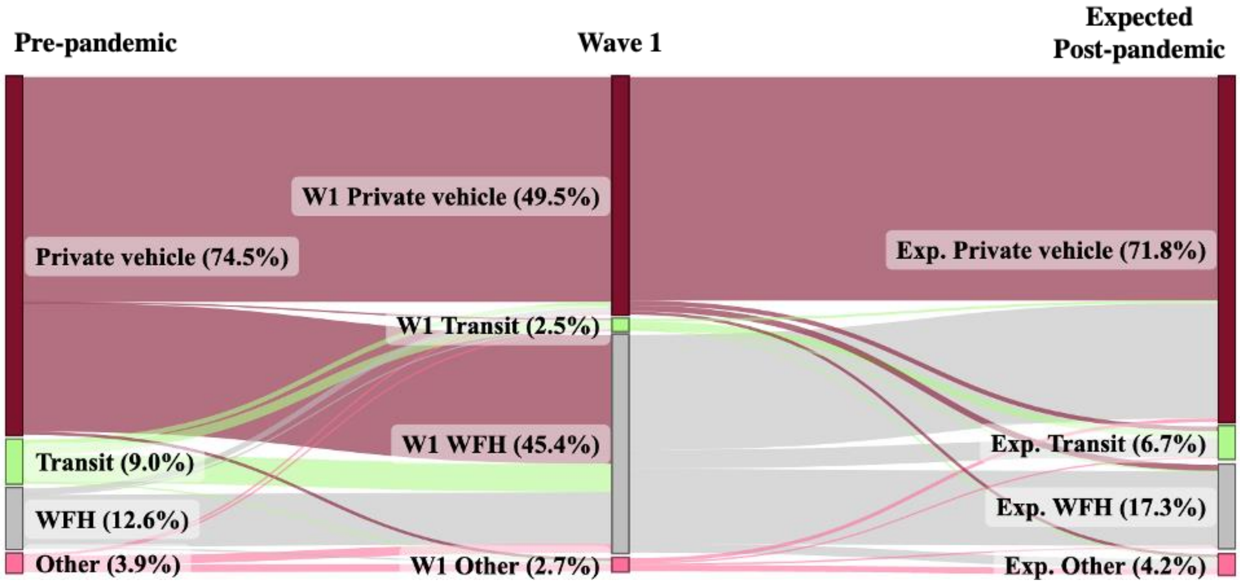

Figure 1 Evolution of Commute Mode Choice (N=930)

The COVID Future Survey includes a rich set of attitudinal statements with a view to elicit information about attitudes, perceptions, preferences, and values. As mode choice may be influenced by such variables, latent attitudinal constructs were developed using a confirmatory factor analysis. In particular, based on prior research and the desire to reflect the influence of personality traits on mode choice, two latent attitudinal constructs were specified and estimated. They are *environmental friendliness* and *social interaction propensity*. Each of these latent attitudinal constructs is defined by three attitudinal statements in the survey. Figure 2 presents information about the attitudinal statements comprising each latent factor and their distributions. The environmental friendliness construct is defined by the degree to which individuals are worried about the environment and are interested in an environmentally friendly lifestyle. The social interaction propensity is defined by indicators that capture the extent to which individuals enjoy interactions at the workplace, like seeing and being around people, and like to be outside. It is hypothesized that individuals who are more environmentally friendly and interested in social interactions would be more likely to choose shared modes of transportation such as public transit.

A confirmatory factor analysis employing principal component analysis with varimax rotation was conducted to develop the factors and compute factor scores for each observation in the sample. In the interest of brevity, detailed results of the factor analysis are not furnished here.

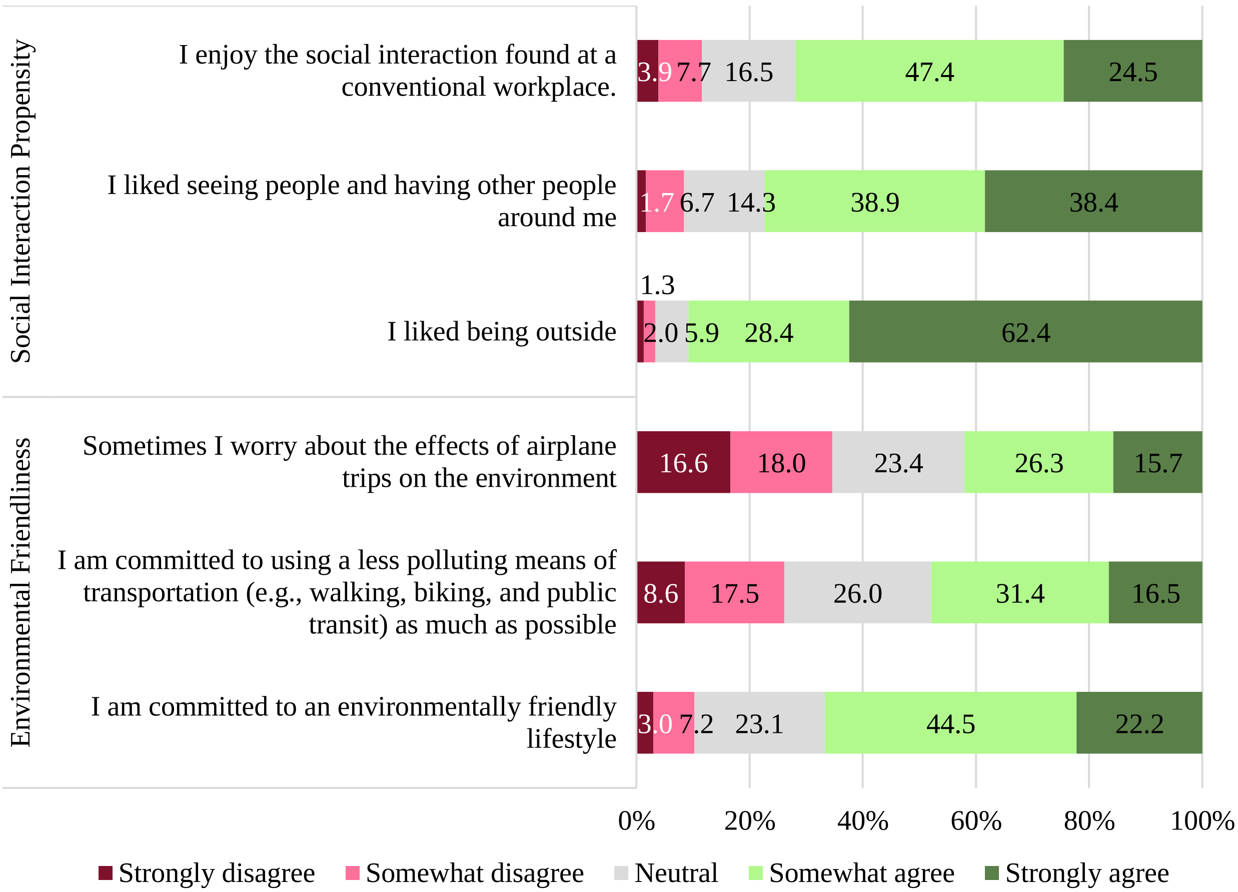

Figure 2 Distribution of Attitudinal Indicators of Latent Factors (N=930)

METHODS

This section offers an overview of the model framework and methodology. The data format and model structure are presented first, and a brief overview of the modeling methodology is presented second.

Data Format and Model Structure

The objective of this study is to model the evolution of mode use over time with a specific interest in the transitions experienced by transit. Thus, the aim of the modeling exercise is to compute the COVID-effect, i.e., the impact of COVID on mode use, and to determine the extent to which mode use will return to pre-pandemic levels/patterns once the pandemic has faded.

Because of the panel nature of the data set and the desire to compute COVID effects and post-COVID recovery, the data set needs to be stacked in a specific way to reflect three different time points (before, during, and after COVID-19 pandemic). The stacked data set has 930 x 3 = 2790 records, with three rows for each individual. The three rows correspond to the three time periods and include information about socio-economic and demographic attributes, attitudinal constructs, and mode choice. While the socio-economic, demographic, and attitudinal variables are assumed to be static across the three time periods, the mode choice variable is specific to the time period and may vary for the same individual across time periods. The data set includes a binary wave indicator for each time period, thus signifying whether a particular observation for an individual corresponds to the pre-, during-, or post-pandemic period. Finally, there are a series of columns in the stacked data set representing interaction effects between exogenous variables and time period (wave) indicators. By configuring the data set in this fashion, it is possible to distinguish between three possible effects: *baseline exogenous variable effect* (no period effect); a pure *period effect* (no exogenous variable effect); and an *interaction effect*, which may be viewed as a combined exogenous variable and period effect. It is possible to have multiple significant effects shaping the evolution of commute mode over time; by taking an algebraic sum of multiple effects, the net COVID effect can be computed. These effects will be discussed and presented in greater detail in the context of the presentation of model estimation results. A simplified version of the model structure is shown in Figure 3.

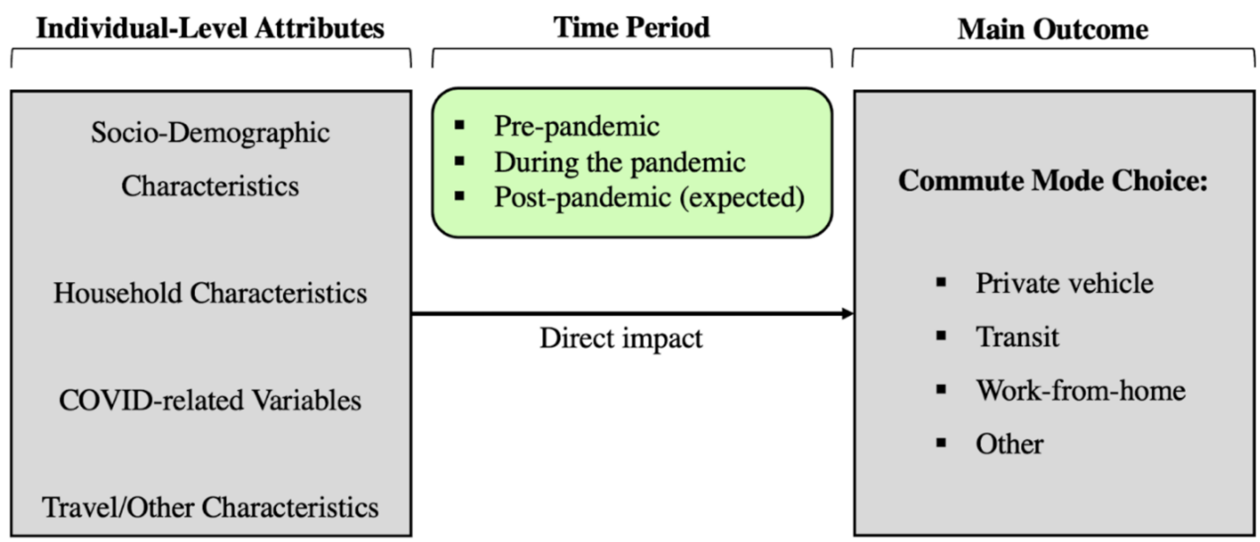

Figure 3 Model Structure and Framework

Model Methodology

The endogenous variable in this study is a multinomial mode choice variable with four alternatives. As such, there is only one dependent variable. The modeling methodology employed in this study is a special case of a panel multinomial probit model with four alternative mode choices, collected for three time periods, namely, before, during, and after (expected) the pandemic. The model formulation is somewhat complex (even in the context of a single endogenous choice variable) primarily due to the three-wave panel nature of the data set. The econometric formulation is rather mathematically notation-intensive and it would be impossible to render justice to the formulation within a brief write-up. As the model formulation is not necessarily of central importance for interpreting model estimation results presented in the next section, the write-up of the formulation has been included in the appendix for the interested reader.

MODEL ESTIMATION RESULTS

This section presents a detailed discussion of the panel multinomial probit model estimation results. The model is estimated in a computationally efficient manner using analytical approximations proposed by Bhat (2018). Table 2 presents the estimation results together with goodness-of-fit statistics. The “other” mode category is treated as the base, with utility equations for private vehicle, transit, and work from home depicted in the table. The three time periods are denoted as pre-COVID, during-COVID, and post-COVID to provide clarity in interpretation.

The estimation results show that there are significant period effects even after controlling for a host of socio-economic, demographic, and attitudinal variables. The during-COVID indicator (effect) is negative for private vehicle and transit and positive for work-from-home (WFH). This is consistent with expectations in that, at the height of the pandemic, offices closed and everybody who could work from home was asked to do so. This greatly reduced the use of private vehicle mode for commuting to work. This also resulted in a reduction in transit usage, although lower transit patronage may have also stemmed from fear of the contagion (Javadinasr et al., 2021). What is interesting to note is that the post-COVID effect is statistically insignificant, suggesting that the post-COVID era will be marked by a recovery of private vehicle and transit mode use (at least for this panel sample) to levels that are somewhat close to those seen in the pre-pandemic era. However, work-from-home will persist; the positive coefficient is marginally significant for the post-COVID effect.

Latent constructs play a significant role in shaping mode choice. Environmental friendliness is associated with a lower propensity to use the private vehicle, a finding that is also reported in prior literature (Kim et al., 2017; Magassy et al., 2022). The social interaction propensity factor is associated with a significant negative effect on work-from-home; indeed, those who enjoy social interactions are less likely to embrace a work-from-home modality in the post-pandemic period. Environmental friendliness affects mode choice differentially across periods. In the pre-COVID period and post-COVID period, it has a negative effect on work-from-home; and in the during-COVID period, it has a positive effect on private vehicle use. In a pre-COVID and post-COVID period, they are more likely to work in the office (due to their job responsibilities), while in the during-COVID period they are more prone to telecommuting (because their job allows them to do so) or using private vehicle as the commute mode (to minimize risk of contagion).

Table 2 Estimation Results for Commute Mode Choice and Time Period Effects

	Commute mode choice (base: other)					
	Private vehicle		Transit		WFH	
Explanatory variables (base category)	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Wave Effect (Pre-COVID)						
During-COVID	-0.28	-1.45	-0.50	-1.58	0.96	3.30
Post-COVID	-0.05	-0.77	-0.09	-0.84	0.35	1.63
Latent constructs						
Environmental friendliness	-0.48	-6.42	na	na	na	na
Environmental friendliness: Pre-COVID	na	na	na	na	-0.20	-1.93
Environmental friendliness: During-COVID	0.17	1.98	na	na	na	na
Environmental friendliness: Post-COVID	na	na	na	na	-0.29	-3.37
Social interaction propensity	na	na	na	na	-0.14	-2.67
Age (*)						
18-40 years: During-COVID	-0.25	-2.22	na	na	na	na
71 years or older	0.53	2.42	na	na	na	na
Race (*)						
Black	0.83	2.99	1.28	3.69	0.58	2.17
Asian or Pacific Islander	-0.25	-1.37	na	na	-0.63	-2.77
Asian or Pacific Islander: During-COVID	na	na	na	na	0.65	2.68
Hispanic ethnicity (not Hispanic)						
Hispanic	0.37	2.34	0.61	2.89	na	na
Education (less than Bachelor's degree)						
Bachelor's or graduate degree	na	na	0.43	2.06	na	na
Health Status (not immunocompromised)						
Immunocompromised: During-COVID	na	na	-0.10	-1.13	na	na
Vehicles available in household (*)						
0	-2.67	-7.86	na	na	-0.59	-2.82
1	-0.32	-3.35	na	na	na	na
Household annual income (*)						
Less than $25,000	na	na	na	na	-0.67	-4.01
$200,000 or more: Pre-COVID	-0.38	-2.53	na	na	na	na
Home Type (not an apartment or condo)						
Apartment or Condo	-0.28	-1.86	na	na	na	na
Population density (high pop. density area)						
Low pop. density area (< 2900 persons/sq. mi.)	na	na	-0.76	-4.76	na	na
Commute distance (less than 40 miles)						
40 miles or more	na	na	0.57	1.64	na	na
Constant	1.76	13.27	-0.22	-0.83	0.32	1.34

Data fit measures	Proposed model	Model without correlation and panel effects
Log-likelihood at convergence	-1777.43	-2075.90
Log-likelihood at constants	-3867.76	-3867.76
Number of parameters	53	35
Likelihood ratio test	0.540	0.463
Average probability of correct prediction	0.286	0.227

Note: Coef = coefficient; “na” = not applicable.

*Base category is all other complementary categories for the correspondent variable.

All other socio-economic and demographic attributes present indications that are consistent with expectations. Younger individuals in the 18-40 year age group were less likely to use the private vehicle during-COVID, relative to other age groups – presumably because they are technologically savvy enough to work from home (Reiffer, 2022) and comfortable riding transit because they are not as vulnerable as the elderly to the threat of the virus. Older individuals depict a pure exogenous variable effect in that they are more prone to commuting by private vehicle. When compared to other races, it is found that Blacks are more prone to using private vehicle, transit, and work-from-home (relative to the “other” mode). Asian or Pacific Islanders are less likely, in general, to use the private vehicle as a commute mode or work-from-home (when compared to other races). However, during-COVID, they exhibited a greater propensity to work-from-home relative to other race categories. Hispanics exhibit a greater proclivity towards using the private vehicle and transit modes (pure exogenous variable effect, with no period effect).

Those with a higher education level (Bachlor’s or graduate degree) are found to exhibit a greater proclivity towards using transit; this group of individuals tends to be white collar suburb-to-central city commuters who use premium transit services. The coefficient simply reflects the pure exogenous variable effect. Health status is not found to be statistically significant; however, the negative coefficient on transit use is retained due to behavioral intuitiveness. Those who are immunocompromised are less likely to use a shared mode of transportation such as transit for fear of contracting the virus. The statistical significance of the coefficient may have been adversely affected by the rather modest sample size (less than 1000 observations) in the context of estimating a panel multinomial probit model with three periods and four alternatives. Zero vehicle availability is associated with a lower propensity to use the private vehicle or work remotely; these indivdiuals tend to be lower income frontline workers who rely on transit for their commute (Rho et al, 2020). Indeed, it is found that lower income individuals are less likely to work-from-home, presumably because their jobs are not amenable to remote work (Tahlyan et al., 2022; Mohammadi et al., 2022). An interesting finding is that those with very high incomes ($200,000 or more) were less likely to use the private vehicle as a commute mode in the pre-pandemic period. As noted earlier, these workers are highly educated individuals who used premium transit services to commute from suburbs into offices in city centers. Those residing in apartments are less likely to be auto commuters, possibly due to higher density area that allows use of public transit, walk, and bike (Paleti et al., 2013), while those residing in areas of low population density are less likely to be transit users. Those who are far away from their workplaces tend to be transit users, a finding also reported in the literature (Gao et al., 2019). These are all pure exogenous effects.

The goodness of fit measures are shown at the bottom of the table. The likelihood ratio test shows that the proposed model offers a superior goodness-of-fit compared to the model that ignores correlations and period effects. The average probability of correct prediction is also higher for the proposed model. In general, the model estimation results are consistent with expectations. A number of explanatory variables depict pure exogenous effects; however, a few also depict period effects through period-specific interaction terms. An examination of the error correlation matrix (not presented in the interest of brevity) shows that there are several significant error correlations for specific pairs of choices across time periods. These significant error correlations confirm the appropriateness of using a panel multinomial probit model methodology because it is capable of explicitly accounting for the presence of such correlations. It is clear that there remain correlated unobserved factors that simultaneously impact the choice of different modes of transportation across COVID periods, even after controlling for attitudes. For example, private vehicle in the pre-pandemic period has a significant positive correlation with private vehicle mode choice in the during-COVID and post-COVID impacts. In other words, the unobserved factors that contribute to an individual using the auto mode for commuting in the pre-pandemic era also contribute to the choice of auto in the during- and post-COVID periods. This is consistent with expectations; an individual who is auto-oriented in the pre-pandemic era is likely to remain so in the during- and post-pandemic periods as well.

COMPUTATION OF EXOGENOUS VARIABLE AND COVID SHIFT EFFECTS

The goal of this study is to quantify the effects of COVID on mode shares and to obtain estimates of the extent to which mode shares may rebound to pre-COVID levels. The study is primarily motivated by an interest in understanding the future of transit, given the drop in transit ridership experienced by transit systems across the country. The future of transit is, of course, intricately tied to the future of work and hence the model estimated in this report includes work-from-home as an explicit commute choice alternative. This section presents estimates of commute mode shares for various socio-economic and demographic groups in each of the time periods; the estimates are computed using model estimation results presented in Table 2 and employing a methodology similar to that described by Asmussen et al. (2022). Essentially, the directionality and magnitude of effects are determined using the notion of average treatment effects or ATEs. The average treatment effects constitute the impacts of a treatment applied to an upstream (exogenous) variable on the outcomes of downstream variables that are influenced by the state of the upstream variables. For computing COVID effects across exogenous variables in the context of this study, all individuals in the sample are set to a particular category of an exogenous variable and also set to the base "pre-COVID" state. Then, model estimates of Table 2 may be used to compute the joint probability of all possible multivariate combinations of the outcome variable (mode choice) at the individual level. Average probability of each multivariate combination can be computed from the joint probabilities, and subsequent computation of marginal probabilities for outcomes of interest may be considered to be magnitude effects corresponding to a specific state of the exogenous variable in the pre-pandemic period. The process can be repeated for during-COVID and post-COVID periods, thus enabling the computation of treatment effects for each level of every exogenous variable for the three periods of interest.

The computed effects constitute changes in predicted mode shares for each socio-economic and demographic subgroup in each of the three time periods. Predicted mode shares are presented in Table 3. By comparing mode shares across socio-economic and demographic groups, it is possible to assess exogenous variable effects. More relevant in the context of this study is a comparison across periods, thus enabling the computation of a true period effect for each socio-economic and demographic subgroup. Because this study considers three time periods, a total of three period (i.e., COVID-shift) effects may be considered: pre-pandemic to during-pandemic; pre-pandemic to post-pandemic; and during-pandemic to post-pandemic. The first constitutes the *COVID-shift effect*, the second constitutes the *rebound effect* (the extent to which the final state of the system rebounds to the initial state), and the third constitutes the *recovery effect* (the extent to which changes that occurred due to a disruption are reversed).

Table 3 Commute Mode Shares by Time Period (N = 930)

		Before-COVID Mode share (%)				During-COVID Mode share (%)				After-COVID Mode share (%)			
Variable type	Exogenous variables	PV[1]	Transit	WFH	Other	PV[1]	Transit	WFH	Other	PV[1]	Transit	WFH	Other
Latent construct	ENV[2] 25th percentile	79.7	6.3	11.7	2.4	53.8	2.0	42.1	2.1	76.2	4.3	17.2	2.4
	ENV[2] 75th percentile	68.6	10.7	15.1	5.6	42.9	2.7	51.5	3.0	66.6	7.9	19.6	5.9
	SIP[3] 25th percentile	73.9	8.6	13.7	3.8	48.0	2.3	47.4	2.3	70.8	6.2	19.0	4.0
	SIP[3] 75th percentile	75.9	8.9	11.0	4.2	52.3	2.6	42.3	2.9	73.6	6.6	15.4	4.4
Age (years)	18 to 40	74.3	8.8	12.9	4.1	44.0	2.7	50.4	3.0	71.3	6.4	18.0	4.3
	41 to 70	74.3	8.8	12.9	4.1	51.2	2.2	44.2	2.4	71.3	6.4	18.0	4.3
	71+	84.7	5.7	7.3	2.3	65.7	1.5	31.3	1.5	83.2	4.2	10.2	2.4
Race	Other	74.6	7.8	13.5	4.2	49.8	2.1	45.4	2.7	71.5	5.5	18.7	4.3
	Black	75.2	14.9	9.5	0.4	55.9	5.6	38.2	0.3	74.3	11.8	13.4	0.5
	Asian or Pacific Islander	75.2	10.4	7.1	7.3	42.2	2.4	52.1	3.3	74.1	8.0	10.2	7.7
Hispanic	No	74.3	8.2	13.2	4.3	48.7	2.1	46.6	2.6	71.3	5.9	18.4	4.5
	Yes	77.5	12.5	8.1	1.8	57.8	4.4	36.3	1.5	76.6	9.8	11.5	2.1
Education level	< College degree	76.5	5.6	13.2	4.7	50.1	1.3	45.9	2.7	73.1	3.9	18.3	4.7
	≥ College degree	74.0	9.7	12.5	3.8	49.5	2.8	45.3	2.4	71.3	7.2	17.4	4.0
Respondent is immunocompromised	No	76.5	5.6	13.2	4.7	50.1	1.3	45.9	2.7	73.1	3.9	18.3	4.7
	Yes	74.0	9.7	12.5	3.8	49.5	2.8	45.3	2.4	71.3	7.2	17.4	4.0
Annual income	< $25,000	81.2	9.2	4.7	4.9	64.2	3.5	27.5	4.8	79.9	7.4	7.2	5.6
	$25,000 to $200,000	75.4	8.3	12.7	3.7	49.0	2.3	46.5	2.2	71.4	6.3	18.4	4.0
	> $200,000	65.7	11.0	17.8	5.5	49.0	2.3	46.5	2.2	71.4	6.3	18.4	4.0
Vehicles available in household	0	11.9	28.9	25.9	33.3	4.4	9.2	65.9	20.5	9.5	22.5	36.7	31.4
	1	72.4	8.8	15.1	3.7	45.6	2.1	50.2	2.0	68.9	6.2	21.0	3.9
	2 or more	80.2	6.5	11.0	2.3	55.1	1.6	42.0	1.3	77.7	4.5	15.4	2.4
Live in apt. or condo	No	75.3	8.0	13.2	3.5	49.7	2.0	46.3	2.0	72.3	5.7	18.4	3.6
	Yes	72.5	10.7	11.0	5.8	49.9	3.2	42.9	4.0	70.3	8.0	15.6	6.1
Population density	Low	76.3	5.7	13.1	4.9	50.1	1.2	46.0	2.8	73.1	3.7	18.3	4.9
	Medium-to-High	70.1	15.3	11.5	3.1	48.5	4.8	44.4	2.2	68.6	11.7	16.3	3.5
Commute distance	< 40 miles	74.9	8.4	12.7	4.1	49.7	2.3	45.5	2.5	72.0	6.1	17.7	4.2
	≥ 40 miles	69.9	15.9	11.4	2.7	48.3	5.6	44.0	2.1	68.2	12.6	16.1	3.1

Note: [1] = Private vehicle; [2] = Environmental friendliness; [3] = Social interaction propensity.

In the interest of brevity, the many computed mode share values are not discussed in the narrative. In general, the computed mode shares and the trends they exhibit are consistent with expectations and very insightful. A few highlights are discussed here for illustrative purposes. Environmentally friendly individuals depict lower levels of private vehicle mode share and higher levels of transit and work-from-home share. During COVID, this group (denoted by ENV 75th percentile in the table) dropped transit share, but continued to exhibit the highest level of transit share among all attitudinal segments. In the post-COVID period, this subgroup of environmentally friendly workers exhibits a greater propensity to work-from-home. The transit mode share for this group decreases from 10.7 percent to 7.9 percent (however, the transit mode share remains highest for this environmentally friendly subgroup in the post-COVID era as well). All other mode share trends can be interpreted in a similar fashion. A few noteworthy aspects include the higher dependence on transit among minority groups and those residing in households with no cars. In the pre-pandemic period, those in the highest income group ($200,000 or more) show the lowest private vehicle mode share, and the highest transit and work-from-home shares. In the post-pandemic period, this same group exhibits the largest increase in private vehicle mode share (when compared to other lower income groups, who show a net *reduction* in private vehicle mode share), resulting in post-COVID transit and work-from-home shares that are identical to those of the $25,000 to $200,000 income group. The highest income group exhibits the largest drop in post-COVID transit share and the smallest increase in work-from-share (when compared with pre-COVID numbers). Except for this anomaly, all other socio-economic and demographic subgroups show the expected reductions in private vehicle and transit mode shares (and increase in work-from-home share) during COVID, and a partial – yet healthy – rebound in commute mode shares in the post-pandemic period. In other words, transit will recover reasonably well, but not to the pre-pandemic levels in the foreseeable future. Most transit mode shares across demographic groups in the post-COVID period are about 70 to 80 percent of the values in the pre-COVID period and double or triple the values seen at the height of the pandemic.

STUDY IMPLICATIONS AND CONCLUSIONS

The COVID-19 pandemic has brought about significant changes in human activity and mobility choices. Many have embraced work-from-home, and transit has seen a substantial reduction in patronage. The question on everybody's mind is whether transit will see a recovery in ridership, and if so, to what extent? This study aims to address this question using a novel panel survey data set collected for a representative sample of individuals from across the United States. A sample of 930 workers answered multiple waves of the survey, enabling an examination of pre-COVID, during-COVID, and post-COVID commute mode shares. Because the survey explicitly asked individuals to state what they intend and expect to do (in terms of commute mode choice and work modality) in a post-COVID era, the model developed in this study is able to explicitly reflect expected post-COVID conditions (and model results can then be used to predict commute mode shares in a post-COVID era).

The study involved the estimation of a panel multinomial probit model of mode choice to capture both socio-economic effects and period effects. The multinomial probit model is capable of accounting for the presence of unobserved factors that simultaneously affect the utilities of different modes of transportation. Besides including a host of socio-economic and demographic explanatory variables, the model included two latent attitudinal constructs representing environmental friendliness and social interaction propensity. These latent attitudinal constructs, formulated using a series of related attitudinal statements in the data set, significantly influence mode choice behaviors along expected lines. The model estimates were used to compute treatment effects; through these computations, the study sheds deep insights on the variations in mode shares across socio-economic groups during each of the three different periods and offers predictions of trends in mode share evolution over time for the various market segments. The results are consistent with what is being seen in the real world, in that COVID had a dramatic effect in reducing commute shares for all modes of transportation, with a surge in work-from-home modality.

The findings in the report suggest that transit will recover about 70 percent of its pre-pandemic ridership in the post-COVID era. Private vehicle mode share will remain depressed by a few percentage points when compared with pre-pandemic mode shares. The work-from-home modality gains share on a consistent basis in the post-pandemic era, largely at the expense of both private vehicle and transit modes. While the time horizon of these predictions cannot be stated with certainty, the study findings suggest that transit patronage is likely to remain depressed by about 30 percent for the foreseeable future, in the absence of substantial changes in service configurations. There is, however, some heterogeneity with respect to COVID effects on transit use across socio-economic and demographic groups. The study shows that minority groups and those living in higher density locales and apartments are more likely to exhibit higher levels of transit use recovery in the post-pandemic period. Service enhancements and changes should be targeted towards accommodating the mobility needs of these market segments; such efforts would advance transportation equity and access to destinations for minority groups. Individuals residing in very high income households are found to depict the lowest level of transit share recovery following the pandemic. Individuals in such an income bracket are choice riders to begin with, and the pandemic appears to have had a significant and long lasting impact on their use of transit. Whether or not it is worth investing in efforts to bring these choice riders back to transit remains uncertain, particularly in the absence of deeper insights on why this market segment is eschewing transit in favor of the private vehicle in a post-pandemic era.

The results of the study may be used to inform the design of service attributes and changes that will help accelerate a transit recovery, as well as obtain a realistic picture of future transit ridership. This information will be useful for transit planners and policymakers who are grappling with high degrees of uncertainty surrounding the future of transit; they will be able to formulate strategies, funding streams, and service configurations that are most appropriate for a post-COVID transit reality.

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APPENDIX

Mathematical Formulation of the Panel Multinomial Probit Model for the Current Study

Consider the following panel multinomial probit model with specification of utility for individual *q* and alternative *i* and with '*t*' being an index for choice occasion:

$$U_{qit} = \boldsymbol{\beta}' \boldsymbol{x_{qti}} + \xi_{qti}, \;\; q = 1,\, 2,\, ...,\, Q, \quad t = 1,\, 2,\, ...,\, T,\; i = 1,\, 2,\, ...,\, I. \tag{1}$$

For ease, we assume that all alternatives are available at each choice instance of each individual, and that we have a balanced panel (that is, we have the same number of choice instances from each individual). $\boldsymbol{x_{qti}}$ is a $(L \times 1)$-column vector of exogenous attributes whose first (*I-1*) elements correspond to alternative specific constants for *(I-1)* alternatives (with one of the alternatives being the base alternative) and the remaining variables being the non-constant variables and $\boldsymbol{\beta}$ is an individual-specific $(L \times 1)$-column vector of corresponding coefficients. We also assume that ξ_{qti} is independent and identically normally distributed across *individuals*, but allow a general covariance structure across alternatives for each choice instance of each individual. Specifically, let $\boldsymbol{\xi_{qt}} = (\xi_{qt1}, \xi_{qt2}, ...\xi_{qtI})'$ ($I \times 1$ vector). Then, we assume $\boldsymbol{\xi_{qt}} \sim MVN_I(0, \boldsymbol{\Lambda}_t)$. Note that the covariance matrix $\boldsymbol{\Lambda}_t$ is specific to the choice occasion *t*, i.e., we allow the covariance matrix to be different across choice occasions. As usual, appropriate scale and level normalization must be imposed on $\boldsymbol{\Lambda}_t$ for identifiability. Specifically, only utility differentials matter at each choice occasion. Taking the utility differentials with respect to the first alternative, only the elements of the covariance matrix $\boldsymbol{\Lambda}_{t1}$ of $\tilde{\xi}_{qti1} = \xi_{qti} - \xi_{qt1}$ $(i \neq 1)$ are estimable, and $\boldsymbol{\Lambda}_t$ is constructed from $\boldsymbol{\Lambda}_{t1}$ by adding an additional row on top and an additional column to the left. All elements of this additional row and additional column are filled with values of zeros. For the ease of estimation and simplicity, we restrict the diagonal elements of the matrix $\boldsymbol{\Lambda}_t$ to be one (we are assuming that there are no scale differences between the alternatives; then essentially $\boldsymbol{\Lambda}_t$ is a correlation matrix). Define the following vectors and matrices: $\mathbf{U}_{qt} = (U_{qt1}, U_{qt2}, ..., U_{qtI})'$ ($I \times 1$ vector), $\boldsymbol{U}_q = (\boldsymbol{U}_{q1}, \boldsymbol{U}_{q2}, ..., \boldsymbol{U}_{qT})'$ ($TI \times 1$ vector), $\boldsymbol{\xi_q} = (\boldsymbol{\xi'_{q1}}, \boldsymbol{\xi'_{q2}}, ...\boldsymbol{\xi'_{qT}})'$ ($TI \times 1$ vector), $\boldsymbol{x_{qt}} = (\boldsymbol{x_{qt1}}, \boldsymbol{x_{qt2}}, \boldsymbol{x_{qt3}}, ..., \boldsymbol{x_{qtI}})'$ ($I \times L$ matrix), $\boldsymbol{x}_q = (\boldsymbol{x}'_{q1}, \boldsymbol{x}'_{q2}, ..., \boldsymbol{x}'_{qT})'$ ($TI \times L$ matrix), $\mathbf{V}_q = \boldsymbol{x}_q \boldsymbol{\beta}$ ($TI \times 1$ vector), and $\tilde{\boldsymbol{\Xi}}_{\boldsymbol{q}}$ ($TI \times TI$ matrix). We construct the $\tilde{\boldsymbol{\Xi}}_{\boldsymbol{q}}$ matrix in a specific way. Specifically, for demonstration purpose, let us consider *T*=3, which is actually the case in our empirical context. Then the $\tilde{\boldsymbol{\Xi}}_{\boldsymbol{q}}$ matrix is:

$$\tilde{\boldsymbol{\Xi}}_{\boldsymbol{q}} = \begin{bmatrix} \boldsymbol{\Lambda}_1 & \boldsymbol{\Omega}_{12} & \boldsymbol{\Omega}_{13} \\ \boldsymbol{\Omega}'_{12} & \boldsymbol{\Lambda}_2 & \boldsymbol{\Omega}_{23} \\ \boldsymbol{\Omega}'_{13} & \boldsymbol{\Omega}'_{23} & \boldsymbol{\Lambda}_3 \end{bmatrix} (TI \times TI \text{ matrix})$$

As mentioned earlier, we allow for a different covariance matrix for the utilities in each choice occasion, and these matrices (i.e., $\boldsymbol{\Lambda}_t$ matrices) constitute the block diagonal matrices of $\tilde{\boldsymbol{\Xi}}_{\boldsymbol{q}}$. The off-diagonal block matrices, i.e., $\boldsymbol{\Omega}_{gh}$ (*g*=1,2,…*T*-1; *h*=*g*+1,*g*+2,…,*T*) constitute the panel correlations, i.e., the correlations across choice occasions. For example, $\mathbf{\Omega}_{12}$ accounts for the correlations between the several alternatives across choice occasion *1* and choice occasion *2*. (Note that, consistent with the utility differences structure, elements in the first row and the first column of this matrix is set to zero). However, to impart a parsimonious specification while also imposing a logical identifiable structure on the correlation matrix, we restrict the $\mathbf{\Omega}_{gh}$ matrices to be diagonal only (except for the first diagonal term which is zero, by structure). Essentially, then, the elements in these matrices account for the panel correlations engendered between the *same* alternatives across the choice occasions in the utility differenced form.

Given these definitions, we may write, in matrix notation, $\mathbf{U}_{\boldsymbol{q}} = \mathbf{V}_{\boldsymbol{q}} + \boldsymbol{\xi}_{\boldsymbol{q}}$ and $\mathbf{U}_{\boldsymbol{q}} \sim MVN_{TI}(\mathbf{V}_{\boldsymbol{q}}, \tilde{\tilde{\mathbf{\Xi}}}_{\boldsymbol{q}})$. Let the individual q choose alternative m_{qt} at the tth choice occasion. To develop the likelihood function, define $\mathbf{M}_q$ as an $[T \times (I-1)] \times [TI]$ block-diagonal matrix, each block diagonal being of size $(I\text{ - }1) \times (I))$ and containing the matrix $\mathbf{M}_{qt}$. $\mathbf{M}_{qt}$ itself is an identity matrix of size (I-1) with an extra column of '-1' values added at the m_{qt}^{th} column. Let $\boldsymbol{B}_q = \mathbf{M}_q \mathbf{V}_q$ and $\mathbf{\Xi}_{\boldsymbol{q}} = \mathbf{M}_q \tilde{\tilde{\mathbf{\Xi}}}_{\boldsymbol{q}} \mathbf{M}'_q$. Let $\mathbf{\Lambda} = [\text{Vechup}(\mathbf{\Lambda}_1), \text{Vechup}(\mathbf{\Lambda}_2), ..., \text{Vechup}(\mathbf{\Lambda}_t)]$ and $\mathbf{\Omega} = [\text{Vech}(\mathbf{\Omega}_{12}), \text{Vech}(\mathbf{\Omega}_{13}), ..., \text{Vech}(\mathbf{\Omega}_{t-1,t})]$ where the operator "Vech(.)" vectorizes all the non-zero elements of the matrix/vector on which it operates and "Vechup(.)" indicates strictly upper diagonal elemenets. The parameter vector to be estimated is $\boldsymbol{\theta} = (\boldsymbol{\beta}', \mathbf{\Omega}, \mathbf{\Lambda})'$. The likelihood contribution of individual q is as below:

$$L_q(\boldsymbol{\theta}) = \Phi_{\tilde{J}}((-\boldsymbol{B}_{\boldsymbol{q}}), \mathbf{\Xi}_{\boldsymbol{q}}), \tag{2}$$

where $\tilde{J} = T \times (I-1)$, and $\Phi_{\tilde{J}}(.)$ represents $\tilde{J}$ dimensional multivariate normal cumulative density function (MVNCDF). The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions. Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, we used the analytical methods proposed by Bhat (2018) for approximating this $T \times (I-1)$, integral.