Public Transportation, Transportation Network Companies (TNCs), and Active Modes

from the Pacific Southwest Region University Transportation Center

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January 2022

TECHNICAL REPORT DOCUMENTATION PAGE

1. Project Number PSR-19-34	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Public Transportation, Transportation Network Companies (TNCs), and Active Modes		**5. Report Date** January 31, 2022 **6. Performing Organization Code** N/A
7. Author(s) Jean-Daniel Saphores [ORCID 0000-0001-9514-0994] Farzana Khatun [ORCID 0000-0002-6333-3406]		**8. Performing Organization Report No.** PSR-19-34-TO-035
9. Performing Organization Name and Address METRANS Transportation Center University of Southern California University Park Campus, RGL 216 Los Angeles, CA 90089-0626		**10. Work Unit No.** N/A **11. Contract or Grant No.** USDOT Grant 69A3551747109; TO-033
12. Sponsoring Agency Name and Address California Department of Transportation 1120 N Street Sacramento, CA 95814		**13. Type of Report and Period Covered** Final report (07/01/2020 – 08/31/2021) **14. Sponsoring Agency Code** USDOT OST-R
15. Supplementary Notes Project webpage: https://metrans.org/research/public-transportation-transportation-network-companies-tnc-and-active-modes-an-analysis-based-on-2009-and-2017-nhts		
16. Abstract To better understand how TNCs likely impacted transit ridership before Covid-19, investigate how Covid-19 affected other modes, and elicit obstacles to a resurgence of transit after the pandemic, we analyzed data from the 2017 National Household Travel Survey, and from an IPSOS survey administered in May 2021 for this project. Our Results show that TNCs are attracting younger, more affluent, and better educated urban households, many of whom are also served by transit. Lower-income households who reside in core urban areas served by transit are less likely to switch to TNCs. Our analysis suggests that driving but especially transit and TNCs, could see substantial drops in popularity after the pandemic ends or moves to the background like the flu. Many Hispanics, Asians, and women intend to use transit less. Although walking and biking should increase, many Hispanics, African Americans, and Asians plan on walking/biking less. Key obstacles to a resurgence of transit include insufficient reach and frequency. African Americans and Asians have lingering health concerns, and women are more likely to worry about personal safety. In addition to addressing these concerns, effective transit policies need to be integrated into a comprehensive framework designed to achieve California's social and environmental goals.		
17. Key Words Transportation Network Companies, public transportation, transit, travel behavior, ride share, modes, travel patterns, Covid-19	**18. Distribution Statement** No restrictions.	
20. Security Classif. (of this page) Unclassified	**21. No. of Pages** 108	**22. Price** N/A

Reproduction of completed page authorized

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education, and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

Professor Jean-Daniel Saphores and Ms. Farzana Khatun conducted this research titled “Public Transportation, Transportation Network Companies (TNCs) and Active Modes” at ITS Irvine. The study took place from July 2020 to August 2021 and was funded by a grant from PSR and from Caltrans in the amount of $103,685. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

Acknowledgments

The authors would like to acknowledge the USDOT Pacific Southwest Region University Transportation Center and the California Department of Transportation (Caltrans) for funding this research. They would like to thank Bradley Mizuno, Caltrans task order manager, for serving as the project mentor and providing helpful feedback. The authors also thank the Institute of Transportation Studies (ITS) at the University of California, Irvine, for providing administrative support. Research results from this project have been submitted to several academic journals and will appear in a book edited by ITS faculty.

Abstract

To better understand how TNCs likely impacted transit ridership before Covid-19, investigate how Covid-19 affected other modes, and elicit obstacles to a resurgence of transit after the pandemic, we analyzed data from the 2017 National Household Travel Survey, and from an IPSOS survey administered in May 2021 for this project.

Our Results show that TNCs are attracting younger, more affluent, and better educated urban households, many of whom are also served by transit. Lower-income households who reside in core urban areas served by transit are less likely to switch to TNCs. Our analysis suggests that driving but especially transit and TNCs, could see substantial drops in popularity after the pandemic ends or moves to the background like the flu. Many Hispanics, Asians, and women intend to use transit less. Although walking and biking should increase, many Hispanics, African Americans, and Asians plan on walking/biking less.

Key obstacles to a resurgence of transit include insufficient reach and frequency. African Americans and Asians have lingering health concerns, and women are more likely to worry about personal safety. In addition to addressing these concerns, effective transit policies need to be integrated into a comprehensive framework designed to achieve California's social and environmental goals.

Public Transportation, Transportation Network Companies (TNCs), and Active Modes

Executive Summary

In the years preceding the Covid-19 pandemic, the fall in transit ridership combined with the explosive growth of transportation network companies (TNCs) such as Uber and Lyft led to a rise in urban congestion, additional air pollution and emissions of greenhouse gases, and a reduction in the physical activity of people who would otherwise walk/bike to access transit. The Covid-19 crisis has further deteriorated the health of transit in California. The purpose of this project is to: 1) better understand how TNCs likely impacted transit ridership before Covid-19; 2) explore if transit can be partially modeled as an active mode; 3) investigate the impact of Covid-19 on selected road transportation modes; and 4) elicit some of the obstacles likely to hinder a resurgence of transit after the Covid-19 pandemic.

To answer these questions, we relied on two datasets. The first one is the 2017 National Household Travel Survey (NHTS), which collected travel, vehicle, and socio-economic data from 129,969 U.S. households between April 2016 and April 2017. The second dataset was collected by IPSOS in May 2021 from the California subset of KnowledgePanel.

To understand how TNCs likely impacted transit ridership before Covid-19, we contrasted households who use public transit, TNCs, and both by analyzing mode use data collected in the 2017 NHTS. Our cross-nested model results show that transit and TNCs target households who share common socio-economic characteristics and reside in similar areas. These households are more likely to include Millennials and post-Millennials, have higher incomes, advanced degrees, no children, and fewer vehicles than drivers. Compared to public transit, TNCs provide more convenient and faster point-to-point service, so increasing the exposure of these households to TNCs may hasten their exodus away from transit. Many low-income households (often members of disadvantaged groups) also reside in core urban areas served by transit. However, we found that these households are less likely than higher-income groups to take both TNCs and public transit. This is not surprising since TNCs are typically not the cheapest transportation option. Partnerships between transit and micro-mobility providers could prove attractive to these households if pricing is right and if micro-mobility is offered in secure areas in minority neighborhoods. We note that African American and Asian households are also less likely to use TNCs (all else being equal), which suggests racial discrimination.

To explore whether public transit could be treated as a "pseudo active transport mode" that shares utility with active modes in a discrete choice framework, we calculated travel distance and travel time using the HERE app. We then compared three models (multinomial logit, nested logit, and cross-nested logit) while controlling for a broad range of variables known to influence mode choice for commuting. We found that our simplest model (a multinomial logit model) outperforms the other two. Moreover, for our dataset, taking transit is best

modeled separately (i.e., not grouped with walking and biking in a nesting structure). Our results highlight the importance of travel time between home and the workplace. Moreover, inadequate facilities refrain commuters from walking and biking even in dense urban areas. This highlights the importance of developing good walking and biking infrastructure.

To investigate the impact of Covid-19 on selected road transportation modes, we estimated logit models that explain Californian's intentions of using different modes (driving, transit, walking and biking, and TNCs) for any travel purpose after the pandemic is over (or fades in the background, like the flu). While between 68% and 70% of respondents anticipate no mode change, three modes could see substantial drops in popularity: driving, transit, and TNCs. A decrease in driving would reduce VMT and help the state achieve its greenhouse gas reduction target. However, it is not possible to say at this point if the intentions of the 19.5% of our respondents who plan to drive less will be sufficient to offset the other 12% who intend to drive more. Results for transit are grim: over 26% of our respondents intend to use transit less after Covid-19 (only 4.7% plan to use it more). This drop disproportionately affects Hispanics, Asians, and women, many of whom were sustaining transit ridership before the pandemic. Likewise, respondents from a broad range of backgrounds intend to use TNCs less after Covid-19. A silver lining is a substantial uptick in intentions to walk and bike more (+23.1%), with just under 7% of our respondents announcing opposite intentions. Surprisingly, results were mixed among Hispanics, African Americans, and Asians, with relatively large percentages of respondents in each of these groups stating their intent to walk less.

To elicit some of the obstacles likely to hinder a resurgence of transit after Covid-19, we estimated logit models to explain the main reasons why Californians were reluctant to use transit in 2017 and why they may not take transit after the pandemic. The main reason why Californians will not take transit is well-known: they prefer to drive, which reflects that driving offers more flexibility and is perceived as safer than taking transit. The other most popular reasons ("no stops near destinations of interest," "service not frequent enough," and "service takes too long") reinforce that point. The limitations of transit's reach and frequency are especially of concern to younger adults, more educated people, and more affluent households. A key priority for transit agencies should therefore be to increase the frequency of their service, develop their network and extend their reach by addressing the first- and last-mile problems. To attract younger riders in urban areas, one possibility would be to offer micro-mobility services (e.g., shared e-scooters, bikes, or e-bikes) directly or via partnerships. To address the health concerns of African American and Asian riders, transit operators should adopt best practices to promote health, and publicize their efforts. It is also essential to address public safety concerns, which are particularly important to women.

Overall, transit policy needs to be integrated into comprehensive policies designed to achieve California's transportation, social, and environmental goals. These policies need to account for the generalized costs and the characteristics of all the transportation options available. They should strive to better price urban spaces (i.e., parking) and the externalities of private motor vehicles (e.g., air pollution and greenhouse gas emissions) while fostering new alternatives to achieve more equitable mobility. Although this study is just a limited snapshot in a period of major changes, we hope that it will be useful to California's transit agencies and to Caltrans.

INTRODUCTION

In the years preceding the Covid-19 pandemic, transit ridership fell in Southern California despite substantial investments, while Transportation Network Companies (TNCs) were experiencing explosive growth. The decline of transit and the rise of TNCs had adverse social consequences, including increased congestion in urban areas, additional air pollution, and reduced physical activity of people who would otherwise walk/bike to access transit. The Covid-19 crisis has further aggravated the health of transit in the state. Due to limited data on TNCs, research on these consequences is limited. In this context, this project analyzes four questions related to Transit, TNCs, and active modes (walking and biking):

1. To what extent have TNCs displaced transit users in California? In this task, we investigate the difference between the travel behavior of two transit user groups defined by the availability or the lack of availability of TNC services. Our treatment group is households with access to both transit and TNCs in the 2017 NHTS; our control group is households with access to transit in the 2009 NHTS (TNCs were not available then). We use Propensity Score Matching (PSM) to match households in the two groups based on socio-economic and land-use variables.

2. To what extent does public transportation contribute to active modes in California? Transit is partly an active mode because the first and last mile of transit trips include walking/biking. This dimension of transit has not yet been explored in the context of California. We evaluate this nature of public transportation through a cross-nested logit (CNL) model, where transit is a part of both active and non-active nests.

3. What is the impact of the Covid-19 crisis on transit, active modes, and TNCs, based on a random survey of Californians organized by IPSOS (a leading polling firm that maintains a large panel representative of the US population) for this research project? This survey asked respondents how their use of various modes (driving, transit, walking/biking, and TNCs) was likely to change after the Covid-19 pandemic compared to the immediate pre-pandemic period.

4. How can public transit use be promoted in California? To answer this question, we analyzed answers to the 2017 NHTS question, "What keeps you from taking transit (or taking transit more often) to your destination(s)? Please SELECT THE TOP THREE reasons." This question was asked only to Californians who are at least 16. We also analyzed answers to the following questions asked in the IPSOS survey conducted for this project: “After the Covid-19 pandemic is over and assuming pre-Covid-19 transit schedules and prices, what would prevent you from taking transit more (local buses, commuter trains, subway, trams, or ferries) for any travel purpose? Please rank your top three reasons (from 1=most important overall to 3=3rd most important).” We analyzed the top answers to each question using a logit model. Our findings suggest a series of actions that California transit agencies could use to jump-start transit ridership.

We hope that our results will shed some light on the impact of TNCs on transit and help better understand transit ridership. We also hope that our results will help gauge how the perception of transit was affected by the Covid-19 pandemic so that transit agencies can take measures to stem the decline of transit ridership in California and help the state achieve a more sustainable and equitable transportation system.

I. BEST FRENEMIES? A characterization of TNC and transit users

INTRODUCTION

The emergence in 2009 of on-demand, door-to-door ride services from Transportation Network Companies (TNCs) such as Uber and Lyft, has created new and very popular mobility options, stirring competition with other modes, especially taxis and public transportation. Building on their success, Uber and Lyft launched in 2014 UberPOOL and Lyft Line in selected metropolitan areas. These new services allow travelers to share their rides with others at cheaper rates than UberX and Lyft Classic (Alemi et al. 2018b). The overall expansion of their services and these additions have further fueled the explosive growth of TNCs, which were estimated to have transported 2.61 billion passengers in 2017, up 37% from the year before (Schaller 2018). While many have applauded the rise of TNCs, some have raised concerns about their impact on public transportation (Malalgoda and Lim 2019), traffic congestion (Erhardt et al., 2019), air quality, and vehicle miles traveled (Alemi, Circella, and Sperling, 2018; Schaller 2018; Sperling 2018), casting TNCs as a threat to the sustainability of urban transportation systems.

The reluctance of TNCs to share their data publicly makes it difficult for policymakers and researchers to analyze the impacts of TNCs on other modes, particularly transit. To circumvent this obstacle, we analyzed data from the 2017 National Household Travel Survey (NHTS) to examine the claim that TNCs are attracting riders who would have otherwise taken public transportation (or walked/biked, or not traveled) (Alemi, Circella, and Sperling, 2018; Schaller 2018) by contrasting the characteristics of public transportation users with those of TNC users.

While several papers have examined TNC users and the possible impacts of shared mobility on transit (Blumenberg et al., 2016; Alemi, Circella, & Sperling, 2018; Schaller, 2018), to the best of our knowledge, this study is the first to formally contrast transit and TNC users using a multivariate model. The investigation of differences between transit and TNC users should be helpful to transit agencies tempted to substitute TNCs for transit in areas where transit is declining or to extend the reach of transit, but it may also highlight the risk for transit agencies to form partnerships with TNCs. Another contribution of this study is our household-level analysis that accounts for intra-household dependencies of mode choice, which have often been ignored in the transportation literature.

After reviewing selected papers that characterized transit and TNC users, we motivate our model variables and summarize our modeling approach. We then discuss our results, summarize our conclusions, mention some limitations of this work, and suggest future research directions.

LITERATURE REVIEW

This section reviews selected papers that characterized transit users and TNC users. We focus on studies conducted in the U.S. and Canada because of differences in context with other parts of the world. Table I-1 summarizes the papers discussed below.

Characteristics of Transit Users

One strand of the literature has explored the characteristics of transit riders for different forms of transit (bus, light rail, heavy rail, commuter rail) and the location of their residence (urban vs. sub-urban area) (Myers 1997; Garrett and Taylor 1999;) while another strand has distinguished between captive and choice riders (Polzin et al., 2000; Krizek & El-Geneidy, 2007).

In the 1990s, researchers explored what type of transit service users selected based on their home location, income, gender, and race. Garrett & Taylor (1999) reported that core city dwellers, who were primarily low-income, female, non-Caucasian (mostly African Americans), and young adults, relied more on buses and light rail transit (LRT) than other demographic groups. In contrast, suburban riders chose predominantly commuter rail, and they were primarily Caucasian, male, and belonged to higher-income households (Garrett and Taylor, 1999). Other studies confirmed these findings (Myers 1997) and categorized riders into captive (i.e., people for whom transit is the only option) and choice groups (i.e., people who could use other modes, such as driving their own vehicle). For example, after analyzing data from the 1995 NPTS, Polzin et al. (2000) found that captive riders mainly were composed of the elderly and children, lower-income group, people with physical challenges, and families who either could not meet their travel needs via motor vehicles or did not want to own cars. Conversely, choice riders were more diversified and generally more affluent (Polzin et al., 2000).

The 2000s saw a plunge in transit ridership, especially for buses, but passenger characteristics mainly remained unchanged compared to the previous decade (LaChapelle 2009; Taylor and Morris 2015). This fall was associated with heavy investments in rail projects, which targeted more affluent suburban choice riders, to the detriment of bus transit, which was serving primarily poorer and minority communities (Taylor & Morris, 2015). In its investigation of the profile of transit riders during the 2000s, the APTA's 2007 report characterized its main patron group as adults, predominantly women, Caucasian (for rail but not for buses), employed, members of households with an annual income between $25,000 and $49,999, and most likely to be composed of two-members with no motor vehicles (Neff and Pham 2007).

Table I-1. Summary of Selected Studies

Study	Data source and Method	Variables	Key findings
Characteristics of Transit Users			
Garrett and Taylor (1999)	• Review of secondary sources: journals, reports, articles • National Personal Transportation Surveys (NPTS) • American Public Transportation Association	Demographic profile of transit users. Financial information about transit (e.g., subsidies).	• Core city dwellers who are primarily low-income, female, non-Caucasian (primarily African Americans), and young adults, rely more on buses and light rail. • Suburban riders choose predominantly commuter rail; they are primarily Caucasian and male, with higher incomes.
Polzin et al. (2000)	• 1995 NPTS • Descriptive analysis	Transit use frequency, population density, household income, metropolitan statistical area categories, urban classification, vehicle ownership.	• Captive riders are mainly elderly, children, lower-income groups, people with physical challenges, and families who either could not meet their travel needs using cars or do not want to own cars. • Conversely, choice riders are diverse but are generally more affluent.
Kim et al. (2007)	• St. Louis Metropolitan area, U.S. • Multinomial logit model	Socio-economic: age, occupation, gender, race. Mode: pick-up and drop off option, bus, and walking	• People who take the bus to reach transit stations are more likely to live in a commercial area and to be female, African American, a full-time student, and have a middle income ($15K-$24.9)
Krizek and El-Geneidy (2007)	• Twin cities: Minneapolis and Saint Paul • Transit users survey in 2001 and non-users survey in 1999 • Factor and cluster analysis	Driver's attitude, customer service, transit service types, reliability, value of travel time, opinion about transit cleanliness, comfort, safety.	• Choice riders value travel time, reliability, safety, convenience, parking availability, and other ride facilities near transit stations.

Neff and Pham (2007)	• 2007 APTA report • Onboard survey findings • Descriptive Statistics	Age, race, income, gender, education, driving license, employment status, reasons for choosing transit.	• Most likely public transportation stakeholders are adult, women, Caucasian (for both rail and road modes), households with an income between $25,000 and $49,999, employed, and predominantly two-members and zero-vehicle households.
Taylor & Morris (2015)	• 2009 NHTS, APTA, NTD and primary survey of 50 transit agencies • Descriptive analysis	Age, race, income, vehicle miles, number of unlinked passenger trips, transit subsidies.	• Lower income group, African Americans hold the highest share among bus riders. • Higher-income groups and Caucasians mostly prefer commuter rail transit.
Brown et al. (2016)	• 2001 and 2009 NHTS • Smart Location Data (SLD) from the U.S. EPA • Cohort model and logistic regression	Age, gender, race, ethnicity, employment status, life cycle, household size, residential density, income, transit supply index, birth cohort indicators.	• Young adults use transit services, but as they grow older, they tend to shift from transit to cars due to changes in family structure.
Clark (2017)	• APTA report (a compilation of 211 published reports of 163 transit systems) • Descriptive statistics	Age, race, income, gender, education, driving license, employment status, reasons for choosing transit	• Transit users are primarily female, 25-54, employed, educated, minorities, and belong to either low- or high-income groups.
Characteristics of TNC users			
Alemi et al. (2017)	• Same dataset as (Alemi *et al.*, 2018) • One-way ANOVA and binary logit model	65 attitudinal statements related to land use, the environment, technology, government role, car ownership, frequency of using TNC services	• Land use diversity and centrality are positively associated with greater TNC adoption. • Long-distance travelers, particularly air travelers, are more likely to use TNCs.

Leistner & Steiner, (2017)	• Pilot study conducted in Gainesville, FL, to facilitate the transportation needs of older adults (60+) • 40 adults completed 1,445 trips covering 8,119 miles. • Descriptive analysis	Sociodemographic: income level, marital status, age, gender, race, living arrangements; travel information: number of social, shopping, medical and service trips; trip cost, distance, & time.	• Primary use of traveling by Uber was shopping and recreation. • On average, these trips were three times faster than similar transit trips. • Uber may positively impact the mobility of older adults and may be a feasible alternative to transit.
Clewlow & Mishra, (2017)	• Seven major U.S. metropolitan areas • 4,094 respondents: 2217 in dense, urban neighborhoods and 1877 in suburbs.	Travel attitudes, neighborhood, technology, environment; household demographics; residential location; use of shared mobility services, vehicle ownership and preferences.	• TNC adopters have a lower level of vehicle ownership than non-adopters, but they are more likely to own a private vehicle than transit users. • TNC users are younger, more educated, with a higher income, and live in denser urban areas
Alemi, Circella, & Sperling (2018)	• Online survey of 1,191 millennials and 964 Generation Xers. • Quota-based sampling approach of six major regions in California.	Attitudes, preferences, lifestyles, technology adoption, residential location, commute and non-commute travel, vehicle ownership, frequency of TNC use, demographic factors.	• Millennials are more likely to adopt and use TNCs. • Uber/Lyft are user-friendly (less waiting time and easy to arrange rides) • Uber/Lyft can be substitutes for transit trips and walking/biking.
Alemi, Circella, Mokhtarian, et al. (2018)	• Same dataset as (Alemi *et al.*, 2018) • Ordered probit and zero-inflated ordered probit model	Socio-demographic characteristics. Built environment; technology adoption and use; travel behavior; vehicle ownership.	• Land use diversity and density impact frequency of TNC use. • Tech-oriented individuals are more likely to use TNCs. • Individuals with a strong preference for private vehicles are less likely to use TNCs frequently.

Hall et al. (2018)	• 196 MSAs • National Transit Database, newspaper articles, press releases, social media posts. • Difference in differences.	Transit ridership, Uber entry and exit, and a variety of controls.	• Uber is complementary to transit and increases ridership by 5%
Sikder (2019)	• 2017 NHTS • Descriptive statistics and ordered logit model	Personal: gender, age, student status, ethnicity, education, employment status, driver status. Household: drivers, workers, income, vehicle ownership, size. Land use: urban/rural; car share and bike share programs; transit use.	• Frequent TNC users (>= four rides over 30 days) are primarily male, younger, college degree holders, full-time workers with flexible schedules, and belong to higher income and vehicle deficit households. • African Americans are less likely to adopt TNCs. • Those who participate in shared mobility (e.g., car or bike share) and use public transit are more likely to use TNCs -> complementary effect between transit and TNCs.
Grahn et al. (2019)	• 2017 NHTS • Descriptive Statistics; weighted and unweighted linear regression	Age, education, income, number of trips (walk, bike, transit, TNC trips)	• TNC riders tend to live in urban areas; are most likely to be younger, have an advanced degree, and a higher income.
Malalgoda & Lim (2019)	• 50 U.S. transit agencies (2007-2017)	Rail transit effectiveness	• TNCs availability increased rail transit ridership in 2015 • TNCs are neither complement nor substitutes for bus transit

The profile of transit users has also received attention at the regional level (Kim et al., 2007; Krizek and El-Geneidy, 2007). For example, Krizek & El-Geneidy, (2007) investigated the habits and preferences of "potential transit choice riders." Their cluster analysis of transit users and non-users in the Twin City region led them to conclude that choice riders care particularly about travel time, reliability, safety, convenience, and parking availability near transit stations. After analyzing on-board passenger survey data from the St. Louis Metropolitan area, Kim et al. (2007) concluded that females, African Americans, full-time students, and middle-income people were more likely to use bus transit to reach Light Rail Transit (LRT) stations. While these studies showed that the profile of transit users did not change much compared to the 90s, Brown et al. (2016) reported that adults who prefer transit in their early years tend to shift to cars when they get married and have children, which indicates a life cycle effect on transit use preferences (Brown et al. 2016).

Clark's (2017) synthesis of passenger surveys from 163 transit systems spanning 2008 to 2015 provides a profile of transit users just before and after the emergence of TNCs: during that period, transit users were predominantly 25 to 54 years old, disproportionately members of minority communities (especially bus users), and often (71%) employed. Moreover, they had regular access to at least one vehicle (54%), and they were slightly (55%) more likely to be female. Interestingly, households with lower (under $15,000) or higher annual incomes ($100,000 or more) made up a similar percentage (21% each) of transit users. Moreover, a slight majority (51%) of transit users had a bachelor's degree or graduate education.

Grahn et al. (2019) mainly reported similar results from their analysis of the 2017 NHTS. Their findings suggest that in 2017 transit users were younger, disproportionately Asian or African American, and less likely to own a private vehicle. Moreover, those relying primarily on buses had lower incomes, while rail transit users were more likely to have higher incomes.

Although the U.S. and Canada have much in common, the profile of transit users differs in large cities on both sides of the border because large groups of middle and upper-middle-class households still reside in Canadian urban cores (Foth et al. 2013). Although Toronto has a transit system that strives to serve disadvantaged communities (Foth et al. 2013), the 1996 Canadian census shows that 22% of commuters used public transit (Kohm, 2000), partly to avoid expensive downtown parking (a feature shared by several other large Canadian cities). Moreover, unlike in the U.S., transit ridership in Canada increased between 2017 and 2018 (Hunt 2019). One factor explaining the relatively good performance of transit in some Canadian cities is that younger people use public transit to go to school. For example, Hasnine et al. (2018) reported that female students who travel to downtown Toronto campuses prefer to use transit more than those who travel to suburban campuses, possibly because transit services are not as convenient at the outer edges of Toronto (Hasnine et al., 2018).

Characteristics of TNC Users

Several recent papers have characterized TNC users and their behavior (Alemi et al., 2017; Alemi, Circella, & Sperling, 2018; Alemi, Circella, Mokhtarian, et al., 2018; Clewlow & Mishra, 2017; Grahn et al., 2019; Kooti et al., 2017; Leistner & Steiner, 2017).

Some of these papers focused on TNC use among subgroups of the population. This is the case for Alemi et al. (2018), who analyzed a panel dataset of 1,191 millennials and 964 members of Generation X in California, to understand the factors that foster and hinder the use of TNCs by members of these two generations and the impact of TNCs on other modes. They found that millennials are more prone to using TNCs than their older counterparts because arranging rides with TNCs is more convenient and requires less waiting, although their higher cost may be a deterrent. Moreover, younger individuals, people in households without vehicles or with fewer vehicles than drivers, and multimodal users tend to replace some of their transit trips with TNC service. These findings are in line with those of other studies (Circella et al. 2017; McDonald 2015; Rayle et al. 2014), who focused on the travel behavior of millennials and the impact of emerging technologies on transportation. Alemni et al. (2018a-b) analyzed the same dataset to understand the circumstances under which people are more likely to use TNCs (Alemi et al. 2018a) as well as factors explaining the adoption of TNC services and the frequency of their use (Alemi et al. 2018b). They reported that land-use diversity and centrality are the most important factors explaining the use of TNCs; moreover, individuals who travel long distances by plane are more prone to using TNCs (Alemi et al. 2018a). In addition, land-use diversity and density influence the frequency of TNC use, but sociodemographic variables do not seem to matter. As expected, tech-oriented individuals who rely heavily on mobile apps are more likely to adopt and use TNCs, unlike people with a strong preference for their private vehicles.

A few other studies have explored some potential impacts of shared mobility on vehicle ownership and mode preferences. Based on data from a survey conducted in seven major U.S. cities, Clewlow & Mishra (2017) reported that TNC adopters have a lower level of vehicle ownership than non-adopters. Moreover, they are more likely to own a private vehicle than core transit users. Overall, TNC users are comparatively younger, more educated, have a higher income, and live in denser urban environments. In addition, 9% of TNC adopters disposed of their vehicles, and 26% reduced their driving. Although the reported change in transit use was minimal, Clewlow & Mishra (2017) suggested that TNCs can be a good substitute for bus transit and can complement commuter rail. These results are consistent with other sources (Henderson 2017; Shaheen et al. 2015) concerned with shared mobility and its impact on car ownership.

Similarly, Leistner & Steiner (2017) explored the possibility of using Uber to mitigate the travel challenges of older adults. Using descriptive statistics, they contrasted characteristics (time and distance traveled) of transit and Uber trips. They found that shopping and recreational trips are, on average, three times faster with Uber than with transit, so they concluded that Uber might positively impact the mobility of older adults.

Kooti et al. (2017) investigated the impact of dynamic pricing (i.e., pricing that changes depending on demand) on Uber users' participation and retention by analyzing email data covering 59 million rides taken by 4.1 million users between October 2015 and May 2016 to understand the usage patterns and the socio-economic characteristics of both users and drivers. They concluded that Uber riders tend to be more affluent than people who drive their own vehicles. Moreover, younger users use this service more frequently but for shorter distances than older users, and there appears to be gender parity among Uber riders.

Before the 2017 NHTS, the literature analyzed local, regional, or state data to characterize TNC users (Chen 2015; Rayle et al. 2016; Clewlow and Mishra 2017; Alemi, Circella, and Sperling, 2018; Hampshire et al. 2019), and a nationwide understanding of these users was lacking (Sikder 2019). A couple of recent papers have analyzed data from the 2017 NHTS to paint a profile of TNC users (Sikder 2019; Grahn et al. 2020). Sikder (2019) found that frequent TNC users (>= four rides over 30 days) are primarily male, younger, college/bachelor's degree holders, who work full time but have a flexible schedule, with higher incomes. Moreover, they tend to belong to households with fewer vehicles than drivers. Conversely, African Americans are less likely to adopt TNCs. In addition, those who engage in car and bike-sharing and use public transit are more prone to using TNCs, which suggests complementary between transit and TNCs. Grahn et al. (2019) echoed these findings. To the best of our understanding, these two studies do not appear to have considered whether the respondents analyzed had access to TNCs (which were not as ubiquitous in 2017 as they are now), which might have impacted their results.

Another emerging strand of the literature has been exploring the impact of TNCs on public transportation, but its conclusions are not clear-cut (Rayle et al. 2016; Sadowsky and Nelson 2017; Clewlow and Mishra 2017; Hall et al. 2018; Malalgoda and Lim 2019). Some studies, such as Rayle et al. (2016) or Hall et al. (2018), concluded that TNC trips replaced some transit trips. For example, based on over 2 million responses to intercept surveys, Rayle et al. (2016) concluded that at least half of TNC trips in San Francisco replaced transit and driving trips. Clewlow & Mishra (2017) reported similar findings: according to their analyses, TNCs are associated with a 6% drop in bus use and a 3% decrease in light rail use. By contrast, Hall et al. (2018), who investigated the effect of Uber on public transit ridership in several US metropolitan areas, reported that Uber complements transit and increased ridership by 5% after two years. Likewise, after analyzing 2007-2017 data from the top 50 US transit agencies, Malalgoda & Lim (2019) found that both bus and rail transit effectiveness (an index that measures transit service quality in terms of number of employees, vehicle operating hours, and fuel consumption) declined between 2007 and 2017 and that TNC availability increased rail transit ridership in 2015. Furthermore, according to their year-by-year analysis, rail transit effectiveness limited TNC availability, so overall, TNCs are neither complements nor substitutes for bus transit. Grahn et al. (2019) reported that TNCs were primarily used for rare events, with ~19% of TNC trips for social and recreational events, and that TNC users use public transit at higher rates.

DATA AND METHODOLOGY

Model Variables

The 2017 National Household Travel Survey (NHTS) recruited respondents using stratified random sampling. After a pilot study, the 2017 NHTS was administered to 129,969 U.S.

households between April 2016 and April 2017 (Federal Highway Administration 2018). NHTS 2017 data were organized into four files: person, household, vehicle, and trip files.

To select our sample, we extracted respondents who stated that they have access to both transit and rideshare services if their motor vehicles are unavailable. This question was targeted at people 16 years old or older, who hold a driver's license, and whose household could access at least one motor vehicle. This gave us 31,840 observations. Since travel decisions routinely involve other household members, mode choices of household members are not independent. We, therefore, chose the household as our unit of analysis, which resulted in a sample of 23,947 households.

Dependent Variable

We built our dependent variable by combining data from two questions in the 2017 NHTS person file. The first question investigates the frequency of public transit use during a span of 30 days ending on the survey day of each respondent. The second question asks about the frequency of use of rideshare apps (such as the Uber and Lyft apps) during the same 30-day period. We created four mutually exclusive groups of households to obtain our dependent variable based on whether any household member older than 16 took public transportation or used a TNC during the 30 days ending on their survey day:

- Group 1: at least one household member took public transit, but none rode with a TNC.
- Group 2: at least one household member rode with a TNC, but none took transit.
- Group 3: some household members took transit, and some rode with a TNC; and
- Group 4: no household member over 16 took transit or rode with a TNC.

Explanatory Variables

We selected our explanatory variables based on our literature review and the variables available in the 2017 NHTS dataset. From the person file, we retrieved information about age, race, Hispanic status, educational attainment, the existence of a medical condition that could impair travel, working status (from home, full-time, or part-time), and household members born abroad. After aggregating this information by household, we combined it with data from the household file: household income, lifecycle variables, the number of household drivers and vehicles, and homeownership.

Many studies have considered generations instead of age for explaining household travel preferences (Alemi, Circella, and Sperling, 2018; Circella et al., 2017; McDonald, 2015). We relied on definitions from the Pew Research Center (2018) to create our binary generation variables (birth years are in parentheses): Generation Z (1997 to 2001), who therefore were between 16 and 20 years old in 2017; Generation Y (Millennials) (1981 to 1996); Generation X (1965 to 1980); Baby Boomers (1946 to 1964); and the Silent Generation (born before 1946).

For our household model, a generation variable equals one if at least one household member belongs to that generation and zero otherwise.

The literature also suggests that household educational attainment plays a pivotal role in daily mode choice (Alemi, Circella, and Sperling, 2018; Buehler and Hamre, 2015; Circella et al., 2017; Clark 2017; McDonald, 2015). To capture the level of education of a household, we created a variable that reflects the highest level of education among household adults. Following the 2017 NHTS classification, this led to five binary variables, as shown in Table **I-2**.

Race and Hispanic status may matter for selecting a mode (Buehler and Hamre 2015; Clark 2017). In our sample, a binary household race variable equals one if all members of that household identify as belonging to that race and zero otherwise. The "mixed" category captures the remaining households. Hispanic status was defined similarly. We also created binary variables for household members born abroad, the presence of a medical condition impairing mobility, and working status.

In addition, our model includes common household variables such as the number of workers, household size, life cycle, annual household income, and vehicle ownership, which have all been found to matter for explaining household travel preferences (Alemi et al. 2018b; Buehler and Hamre 2015; Clark 2017; McDonald 2015). To capture household structure, we created five life cycle variables (see Table **I-2**). To represent annual household income, we collapsed the eleven categories in the 2017 NHTS into five binary categories (see Table **I-2**). Homeownership is captured by a binary variable, and household size by a count variable.

As the decision to take transit or a TNC should not depend directly on the number of household vehicles or the number of driver's license holders, but rather on whether a household has more drivers than vehicles, we created a binary variable that equals one if a household has more drivers than vehicles and zero otherwise.

Finally, we added five binary variables that reflect the frequency of smartphone use (daily, weekly, monthly, yearly, and never) since TNCs rely crucially on smartphone apps.

It is well-known that land use is correlated with mode choice (Alemi et al. 2018ab; Alemi, Circella, and Sperling, 2018; Buehler and Hamre 2015). Unfortunately, the 2017 NHTS does not come with location information about the residence or the place of work of respondents to protect their privacy, but it includes some common land-use variables. We used population density (1,000 persons/sq. mile) of the home census tract of households in our sample.

To understand how the inclusion of TNCs may have impacted the patronage of different forms of transit, we created three binary variables to capture the availability of bus, light rail, and heavy rail services for the households located in a core-based statistical area (CBSA). A CBSA is a smaller geographic unit than Metropolitan Statistical Area (MSA), with at least 10,000 people and an urban center. The 2017 NHTS reports information about 53 CBSAs. For each, we gathered information about the availability of bus, light rail, heavy rail, and commuter rail transit from the APTA, which publishes quarterly reports on ridership by transit type for primary cities under the jurisdiction of transit organizations in the U.S. We then added this information to our dataset in the form of binary variables to various kinds of transit for the CBSAs of our respondents.

Summary statistics for our model variables are shown in Table **I-2**.

Econometric Framework

The Multinomial Logit (MNL) is often a starting point for modeling mode choice, but it requires that the Independence of Irrelevant Alternatives (IIA; see Train, 2009) holds, which is not the case here because of the definition of our four groups of households (Panel A of Figure **I.1).** A nested logit (NL) model (Panel B of Figure **I.1**) relaxes the IIA requirement for modes in different nests (Train 2009), but given the structure of our mutually exclusive alternatives, a Cross Nested Logit (CNL) model is more suitable because it allows an alternative to belong to multiple nests. Although it is uncommon, several mode choice studies have estimated CNL models (Ermagun and Levinson 2017; Hasnine et al. 2018; Vovsha 1997). Here, we estimated a CNL model to account for the overlap between "Households who use both transit and ridesharing" with "Households who take transit but not TNCs" and with "Households who use TNCs but not transit." The structure of our CNL model is presented in Panel C of Figure **I.1**.

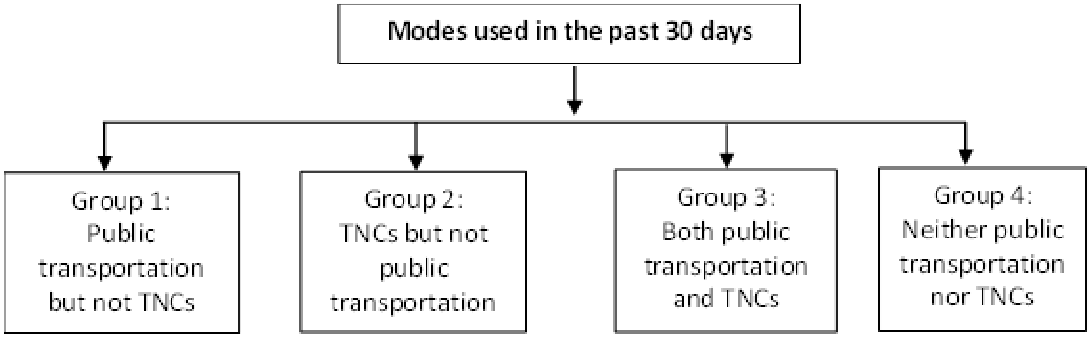
In a CNL model with nests $B_1 \ldots B_N$, an alternative can belong to more than one nest (Train 2009). The extent to which alternative j belongs to nest k is given by the allocation parameter $\alpha_{jk} \geq 0$. Allocation parameters sum to one over nests for a given alternative, i.e., $\sum_k \alpha_{jk} = 1$, which reflects the percentage by which alternative j belongs to nest k ($\alpha_{jk}=0$ indicates that alternative j does not belong in nest k) (Train 2009).

A second type of parameter plays an important role here: the log-sum parameter. Denoted by $\lambda_k \geq 0$, the log-sum parameter for nest k reflects the degree of independence among alternatives within nest k, with a larger value indicating greater independence and less correlation. Log-sum parameter values between 0 and 1 guarantee consistency with utility maximization. However, consistency with utility maximization may still hold for a range of alternatives when log-sum values are above one (Train 2009).

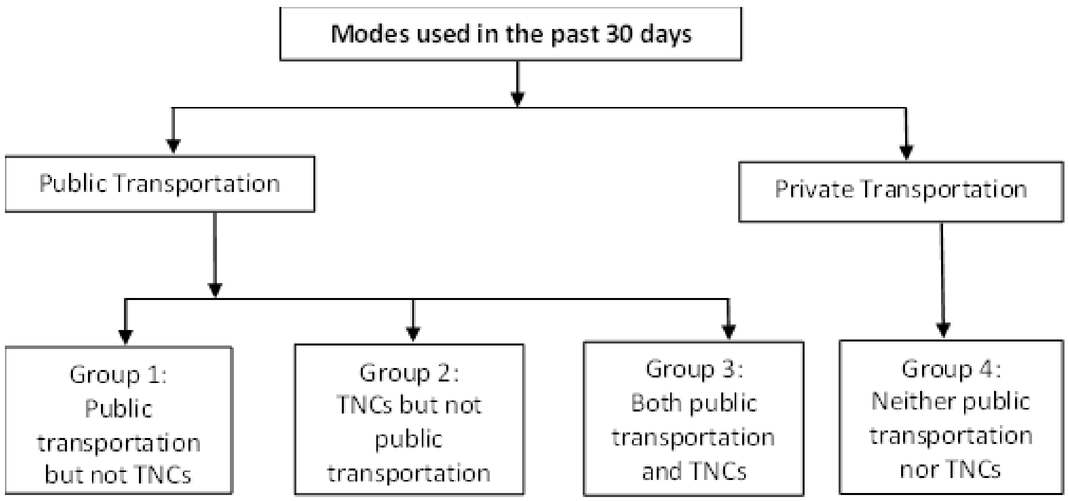
A choice model is defined by the expression of the probability for each alternative "i" available to decision-maker "n" (here household "n"). For the CNL, this expression is given by (Train 2009):

$$P_{ni} = \frac{\sum_k (\alpha_{ik} e^{V_{ni}})^{1/\lambda_k} \left(\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} (\alpha_{jl} e^{V_{nj}})^{1/\lambda_l} \right)^{\lambda_l}} \tag{1}$$

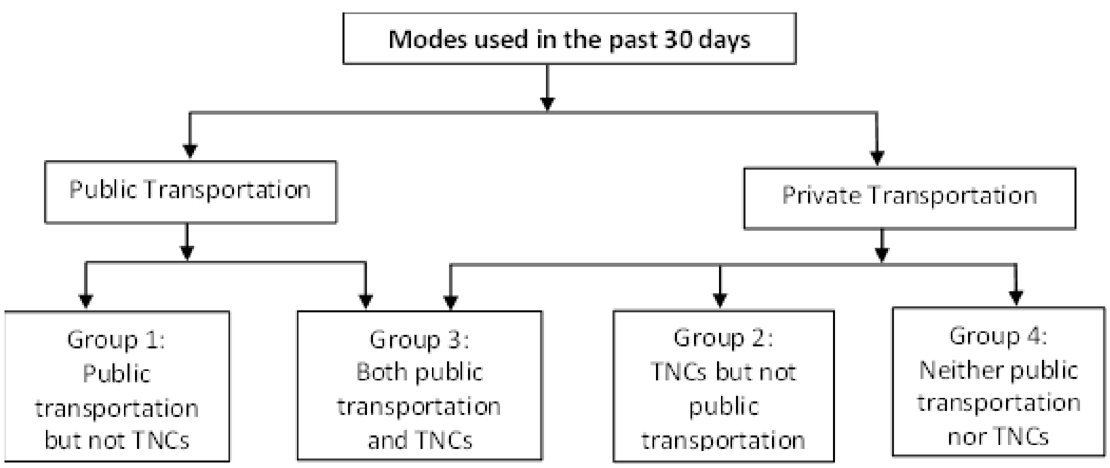
where V_{ni} is the representative utility of alternative "i" for decisionmaker "n". For our models,



Panel A: Multinomial Logit (MNL) structure



Panel B: Nested Logit (NL) structure



Panel C: Cross Nested Logit (NL) structure

Figure I.1 Structure of MNL, NL, and CNL models

Table I-2. Descriptive Statistics (N = 23,947)

Variables	Group 1: Used public transit but not TNCs (N = 2,574)	Group 2: Used TNCs but not public transit (N = 2,485)	Group 3: Used both public transit and TNCs (N = 2,342)	Group 4: Used neither public transit nor TNCs (N = 16,546)	Overall Sample (N = 23,947)
Household					
Generation (see the top of page 13 for definitions)					
At least one adult from Generation Z	2.53%	2.70%	3.33%	1.89%	2.18%
At least one adult from Generation Y	21.87%	48.09%	50.26%	18.56%	25.08%
At least one adult from Generation X	28.40%	32.60%	32.41%	24.80%	26.74%
At least one adult is a Baby Boomers (BB)	47.16%	23.34%	23.23%	47.09%	42.30%
At least one adult is from the Silent Generation	10.06%	2.37%	2.73%	15.33%	12.19%
Household Hispanic Status (Hispanic =1)	5.59%	8.93%	7.47%	6.21%	6.55%
Household Ethnicity					
All household members are Caucasian	82.05%	82.90%	82.11%	85.74%	84.70%
All household members are African American	6.33%	4.35%	4.06%	5.89%	5.60%
All household members are Asian	6.14%	6.04%	7.81%	3.67%	4.59%
Mixed household	5.48%	6.72%	6.02%	4.69%	5.12%
Household maximum educational attainment					
Less than high school	0.62%	0.20%	0.38%	0.93%	0.77%
High school degree	4.74%	1.81%	1.45%	9.89%	7.68%
Some college	15.38%	14.21%	9.82%	27.61%	23.17%
Undergraduate degree	32.40%	40.48%	34.97%	29.96%	31.81%
Graduate or professional degree	46.85%	43.30%	53.37%	31.60%	36.58%
Annual household income					
<$35,000	15.35%	9.86%	9.44%	21.19%	18.24%
$35,000-$74,999	22.96%	22.05%	17.46%	32.63%	29.01%
$75,000 to $124,999	28.09%	27.81%	24.81%	27.09%	27.05%
$125,000 to $199,999	20.05%	21.29%	24.34%	12.93%	15.68%
>=$200,000	13.56%	18.99%	23.95%	6.16%	10.03%
Household life cycle					
One adult, no children	19.77%	28.73%	23.31%	17.24%	19.30%

Two or more adults, no children	28.67%	36.78%	40.31%	21.91%	25.98%
One adult, some children	2.64%	2.90%	3.03%	3.38%	3.22%
Two or more adults, some children	22.26%	21.69%	22.93%	20.00%	20.71%
One retired adult, no children	8.74%	2.17%	2.01%	11.85%	9.55%
Two or more retired adults, no children	17.91%	7.73%	8.41%	25.61%	21.25%
Homeownership (Yes=1)	73.74%	60.93%	56.75%	76.26%	72.49%
Household workers					
No workers	22.22%	7.89%	8.20%	30.80%	25.29%
One worker	38.07%	45.39%	39.07%	37.58%	38.59%
Two workers	34.69%	41.73%	46.33%	27.81%	31.80%
Three or more workers	5.01%	4.99%	6.40%	3.81%	4.32%
At least one member worked from home	12.04%	18.23%	17.21%	9.80%	11.64%
Household has fewer vehicles than drivers	16.16%	7.69%	20.20%	7.14%	9.45%
Work full time/part-time					
At least one adult works full time	56.02%	75.37%	76.56%	48.21%	54.64%
At least one adult works part-time	16.55%	14.69%	13.83%	14.71%	14.82%
At least one member has a mobility impairment	5.67%	2.25%	2.52%	8.21%	6.76%
At least one adult was not born in the US	14.02%	12.19%	16.48%	9.02%	10.62%
Smartphone use					
Daily	80.07%	96.74%	96.88%	74.24%	79.41%
Weekly	5.71%	1.69%	1.75%	5.58%	4.82%
Monthly	2.41%	0.56%	0.43%	2.36%	1.99%
Yearly	1.20%	0.04%	0.17%	1.21%	0.99%
Never	10.61%	0.97%	0.77%	16.60%	12.79%
Availability of transit services					
Household in a CBSA with bus service	66.39%	68.09%	81.04%	42.20%	51.28%
Household in a CBSA with light rail service	58.66%	58.75%	74.30%	33.86%	43.06%
Household in a CBSA with heavy rail service	39.28%	21.93%	50.51%	13.13%	20.51%

Notes:
1. All explanatory variables in our models are binary, except for “Number of household members (Mean: 2.19; S.D: 1.15; Min:1; Max:11)” and “Ln of population density (measured in 1,000/mi^2)” (Mean: 1.11; S.D: 1.31; Min: -3.00; Max: 3.40), which are count and continuous variables, respectively. These two variables are not shown above.
2. CBSA stands for Core Based Statistical Area.
3. Our unit of analysis is the household.

$$\forall i \in \{1,2,3\}, V_{ni} = \beta_{i0} + \sum_{k=1}^{K-1} \beta_{ik} * x_{kn} \tag{2}$$

and $V_{n4}=0$ for identification since only differences in utility matter (and can be estimated). In the above, the β_{ik}s are unknown coefficients, and the x_{kn}s are explanatory variables characterizing decisionmaker *n* (socio-economic and land use characteristics).

If each alternative enters only one nest, the α_{jk} parameters are 0 or 1, and the CNL model simplifies to a NL model. If the log-sum parameters λ_k of a NL model all equal 1, then the nesting logit model reduces to a MNL model.

For a CNL model, the probability that household "n" selects group "*i*" can also be written (Train 2009):

$$P_{ni} = \sum_k P_{ni|B_k} * P_{nk}, \tag{3}$$

where the probability that household "n" falls in nest "*k*" is:

$$P_{nk} = \frac{\left(\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k}\right)^{\lambda_k}}{\sum_{l=1}^{K}\left(\sum_{j \in B_l} (\alpha_{jl} e^{V_{nj}})^{1/\lambda_l}\right)^{\lambda_l}}, \tag{4}$$

and the probability that household "n" selects "i" given that its choice is in nest k is:

$$P_{ni|B_k} = \frac{(\alpha_{ik} e^{V_{ni}})^{1/\lambda_k}}{\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k}} \tag{5}$$

We estimated unknown model parameters via maximum likelihood.

RESULTS

Results were estimated using Stata 15 and BisonBiogeme 2.6 (http://biogeme.epfl.ch/). We checked that multicollinearity is not an issue here as all VIF are substantially below 10.

We first estimated a MNL model (Panel A of Figure I.1), but a Hausman and Suest test showed that the Independence of Irrelevant Alternatives (IIA) does not hold. We then estimated a Nested Logit (NL) structure (Panel B of Figure I.1), but again as expected, a likelihood ratio test rejected that structure in favor of the CNL structure shown on Panel C of Figure I.1. For the latter, log sum and allocation parameters are provided in Table I-3.

AIC and BIC values for all three logit structures showed that the CNL model outperforms both the MNL and NL structures, which vindicated our choice to include households with access to both public transportation and TNCs in an overlapped nest.

CNL Results

Parameter estimates for our CNL model are shown in Table I-3, where Group 4 (households who took neither public transportation nor rideshares) serves as a baseline. Table I-3 also shows the coefficient values for the MNL and NL models to contrast the implication of these three modeling structures. We discuss this point in the robustness section below.

Let us start with the allocation parameters for the overlapping group (Group 3: households who took both transit and TNC in the past 30 days). Their values are 0.673*** and 0.327**, which means that 67.3% of the overlapping group utility comes from the public transportation nest and 32.7% from the private transportation nest. Furthermore, the log sum parameters for the public and private transportation nests are 0.11* and 0.31**, respectively, which are within the required range and suggest that the nesting structure is valid.

Let us now discuss estimated parameters for our explanatory variables. Table I-3 shows that households with post-millennials are more likely to use only transit (0.414*), or only TNCs (0.188***), or both TNCs (0.507***) rather than drive only. Results are similar for households with millennials. For these two groups of households, the magnitude of the coefficients for Group 3 (Households who took both public transportation and TNCs) is comparatively higher than for the first two groups of households. These coefficients are not significant for the Gen X variable. Conversely, households with more Baby Boomers are less likely to use TNCs (-0.180***); likewise, households with more members of the Silent Generation are less likely to use either only TNCs (-0.294***) or both transit and TNCs (-0.316***) than to drive only. This result confirms findings from Blumenberg et al. (2016) and McDonald (2015), who reported that Millennials (along with post-millennials) tend to drive less, own fewer vehicles, and rely more on other modes. These differences can be explained by their preferences, economic status, and life cycle stage (Blumenberg et al., 2016; McDonald, 2015). In contrast, Baby Boomers and Silent Generation members are less likely to use TNCs. A possible reason is that Uber and Lyft vehicles are typically not equipped to easily serve senior citizens or people with mobility impairments simply because Uber and Lyft drivers use their own vehicles.

Ethnicity and Hispanic status play a (limited) role here. Hispanic households appear more likely to take TNCs than to drive only (0.049*). Compared to Caucasian households, both African American (-0.059*) and Asian (-0.064*) households are less likely to use TNCs than to drive only. These two groups of households are also less likely to use both (-0.134* for African Americans and -0.129* for Asians), possibly due to racial bias. Indeed, recent studies have shown that African Americans face higher cancellation rates from TNC drivers, which suggests racial discrimination (Ge et al., 2016).

Education also matters. Households whose highest educational achievement is less than a high school degree do not differ from the baseline (households with some college or an associate degree). However, households with a high school degree are less likely to use either TNCs (-0.160***) or both TNCs and public transportation (-0.178*) than to drive, compared to the baseline. Conversely, households with either undergraduate or graduate degrees are more likely to use either public transit only (0.459*** and 0.696*** respectively), TNCs only (0.106*** and 0.114*** respectively), or both (0.450*** and 0.701*** respectively) than to drive, possibly because they live in more affluent areas that offer both services. These results are consistent with the previous finding that people with advanced degrees prefer rail transit because it is more comfortable, environment friendly, and congestion-free (Clark 2017).

Results for household income reinforce those for education. Compared to the baseline (households with an annual income ranging from $75,000 to $124,999), the two lower-income groups are less likely to take only public transit than to drive (<$35,000: -0.114*; $35,000 to $74,999: -0.239***). To put this result in perspective, recall that all the households in our sample have at least one vehicle available at home. Lower-income groups in our sample are also less likely to use either only TNCs (<$35,000: -0.183***; $35,000 to $74,999: -0.132***) or both public transportation and TNCs (<$35,000: -0.153***; $35,000 to $74,999: -0.260***).

The opposite holds for members of the two higher income brackets, with higher coefficient values for the highest income group. The explanation for this result is the same as for educational attainment (Clark 2017).

As expected, family structure (life cycle variables) influences mode choice. Notably, results show that households without children are more likely to depend less on their cars and more on either public transportation only (0.320***for one adult only, 0.136* for two or more), TNCs only (0.170*** for one adult, 0.115*** for two or more), or both (0.320*** for one adult, 0.147** for two or more). Families with children often have more constrained travel schedules, so they rely more on their household vehicles to fulfill their daily travel needs (Buehler and Hamre 2015). Likewise, larger households are less likely to rely on modes other than their cars (-0.089**, -0.046***, and -0.108*** for public transit only, TNCs only, and both, respectively). Households who own their own home are also less likely to use any of these services (-0.192***, -0.102***, and -0.248*** respectively), likely because homeowners tend to live in suburban areas where public transit and TNC service are scarcer.

The number of workers in the household does not matter here, except that households with three or more workers are more likely to use public transit (0.210*) or both public transit and TNCs (0.246**) than drive only. Moreover, households with members working from home are more likely to take only TNCs (0.131***) that drive only.

As expected, households with members with a physical impairment that limits their mobility are less likely to depend on transit or TNCs or both than on their own vehicles (-0.190**, -0.089** and -0.208*** for households in Groups 1, 2, or 3 respectively). Where people were born does not influence their mode choices in our model. As expected, those who do not use a smartphone daily are less likely to use TNCs than those who use it regularly.

Table I-3. MNL, NL, and Cross Nested Logit Results (N=23,947)

	Multinomial Logit (MNL)			Nested Logit (NL)			Cross-Nested Logit (CNL)		
	Group 1: used public transit but not TNCs	Group 2: used TNCs but not public transit	Group 3: used both public transit and TNCs	Group 1: used public transit but not TNCs	Group 2: used TNCs but not public transit	Group 3: used both public transit and TNCs	Group 1: used public transit but not TNCs	Group 2: used TNCs but not public transit	Group 3: used both public transit and TNCs
Household Variables									
Household members by generation									
Generation Z	0.313*	0.771***	1.027***	0.364*	0.753***	0.969***	0.414***	0.188***	0.507***
Generation Y (Millennials)	0.250**	0.916***	1.163***	0.337**	0.903***	1.095***	0.455***	0.242***	0.561***
Generation X	0.081	0.058	0.156	0.075	0.071	0.146	0.089	0.011	0.101
Baby Boomers	0.169	-0.649***	-0.494***	0.081	-0.571***	-0.453***	0.050	-0.180***	-0.020
Silent Generation	-0.136	-1.072***	-0.876***	-0.220	-0.969***	-0.824***	-0.238	-0.294***	-0.316***
Hispanic status (Hispanic =1)	-0.169	0.193*	-0.005	-0.141	0.161	0.005	-0.130	0.049*	-0.103
Household ethnicity (Baseline = Caucasian)									
African American	0.044	-0.167	-0.349**	0.004	-0.147	-0.299*	-0.103	-0.059*	-0.134*
Asian	-0.050	-0.197	-0.261*	-0.071	-0.189	-0.236*	-0.116	-0.064*	-0.129*
Mixed	0.186	0.200*	0.046	0.177	0.193*	0.070	0.072	0.052*	0.057
Household educational attainment (Baseline = some college or associate degree)									
Less than high school	0.221	-0.444	0.293	0.187	-0.333	0.291	0.216	-0.133	0.266
High school	-0.040	-0.600***	-0.522**	-0.078	-0.540***	-0.477**	-0.121	-0.16***	-0.178*
Undergraduate degree	0.488***	0.374***	0.498***	0.487***	0.387***	0.489***	0.459***	0.106***	0.450***
Graduate or professional degree	0.722***	0.420***	0.817***	0.709***	0.459***	0.784***	0.696***	0.114***	0.701***
Annual household income (Baseline = $75,000 to $124,999)									
<$35,000	-0.144	-0.691***	-0.425***	-0.179*	-0.644***	-0.426***	-0.114*	-0.183***	-0.153**
$35,000 to $74,999	-0.261***	-0.487***	-0.464***	-0.278***	-0.472***	-0.451***	-0.239***	-0.132***	-0.26***
$125,000 to $199,999	0.282***	0.514***	0.649***	0.312***	0.503***	0.614***	0.300***	0.142***	0.339***
>=$200,000	0.502***	1.260***	1.397***	0.591***	1.215***	1.326***	0.549***	0.342***	0.647***
Household life cycle (Baseline = 2+ adults with children)									
One adult, no children	0.389**	0.602***	0.548**	0.420**	0.576***	0.542***	0.320***	0.170***	0.320***
2+ adults, no children	0.164	0.411***	0.325**	0.192*	0.384***	0.323**	0.136*	0.115***	0.147**
One adult, some children	0.049	0.139	0.399*	0.069	0.142	0.361*	0.134	0.041	0.167
1 retired adult, no children	0.175	0.269	0.292	0.191	0.279	0.303	0.140	0.077	0.152
2+ retired adults, no children	-0.259*	0.097	0.162	-0.214	0.069	0.130	-0.157*	0.033	-0.118
Number of household members	-0.060	-0.172***	-0.217***	-0.074	-0.170***	-0.204***	-0.089***	-0.046***	-0.108***

Household owns home	-0.115	-0.386***	-0.562***	-0.151*	-0.376***	-0.522***	-0.192***	-0.102***	-0.248***
Household workers (Baseline = household with no workers)									
One worker	-0.005	0.117	-0.069	-0.012	0.104	-0.047	-0.020	0.030	-0.019
Two workers	0.123	0.044	0.067	0.108	0.055	0.077	0.106	0.014	0.103
Three or more workers	0.173	0.278	0.448*	0.182	0.284	0.421*	0.210*	0.070	0.246**
Working from home (Yes=1)	-0.076	0.500***	0.346***	-0.021	0.454***	0.331***	-0.016	0.131***	0.037
Fewer vehicles than drivers (Yes=1)	1.019***	0.284**	1.156***	0.997***	0.393**	1.099***	0.903***	0.104***	0.896***
Work full time/part-time									
≥ one adult works full time	-0.097	0.085	0.147	-0.075	0.081	0.120	-0.005	0.024	0.025
≥ one adult works part-time	0.062	0.010	-0.069	0.049	0.012	-0.059	0.011	0.001	-0.0002
Medical condition (Yes=1)	-0.177	-0.331*	-0.317*	-0.184*	-0.311*	-0.306*	-0.190**	-0.089**	-0.208***
Non-USA born	0.109	-0.070	0.043	0.090	-0.046	0.043	0.076	-0.020	0.069
Smartphone use (Baseline = daily use)									
Weekly	0.179	-0.750***	-0.581***	0.109	-0.652***	-0.512**	0.055	-0.204***	-0.028
Monthly	0.188	-0.786**	-1.115***	0.102	-0.680**	-0.956**	-0.024	-0.216***	-0.161
Yearly	0.232	-2.721**	-1.255*	0.117	-2.295*	-1.076*	0.035	-0.756***	-0.120
Never	-0.112	-1.803***	-1.983***	-0.204	-1.595***	-1.732***	-0.316***	-0.486***	-0.528***
Land use									
Ln of population density (1,000/mi^2)	0.108***	0.218***	0.263***	0.122***	0.212***	0.244***	0.140***	0.065***	0.152***
Availability of transit services									
In a CBSA with bus service	0.102	0.338***	0.282**	0.127	0.320***	0.276**	0.138**	0.088***	0.161**
In a CBSA with light rail	0.231**	0.326***	0.527***	0.247**	0.329***	0.496***	0.267***	0.085***	0.302***
In a CBSA with heavy rail	1.046***	-0.024	1.096***	1.000***	0.114	1.023***	1.010***	0.012	0.996***
Constant	-2.941***	-2.535***	-3.496***	-2.722***	-2.401***	-3.174***	-2.540***	-0.696***	-2.240***
Log-sum parameters									
Public Transportation nest		NA			0.810***			0.111***	
Private Transportation nest		NA			1 (Fixed)			0.270***	
Allocation Parameters									
Public Transportation nest		NA			NA			0.708***	
Private Transportation nest		NA			NA			0.292***	
Maximum of log-likelihood function		-18616.46			-18615.75			-18592.17	
McFadden Pseudo R^2		0.188			0.000038			0.440	

Notes 1: ****, **, and * indicate p-values < 0.01, < 0.05, and < 0.1, respectively. 2: the sample size is N=23,497. 3: Underlined coefficient values reflect the implication of MNL, NL, and CNL, i.e., how these variables are significant in one structure and not significant in others.

Land use also plays a role here. As expected, households who reside in denser areas tend to use more varied modes (0.140***, 0.064*** and 0.152*** for Group 1, 2, and 3 respectively); the large positive and significant coefficient of Group 3 (households who used both public transportation and TNCs) reflects that there is a lot of overlap between public transit and TNC users. Indeed, Uber and Lyft are primarily present in denser urban environments that typically harbor well-developed public transportation networks. The availability of transit services in a CBSA area tells a similar story. Households who reside in a CBSA with bus, light rail, or heavy rail services use a wider variety of modes (coefficients for all three categories are positive and significant) than households who live in a CBSA without these services (Alemi, Circella, and Sperling, 2018; Alemi et al. 2018a).

Robustness Checks

To select our final model, we considered various functional forms and calculated several goodness of fit measures (AIC, BIC, and count R^2). In all instances, the CNL models we estimated outperformed both MNL and NL models with similar variables. We also explored models with interaction terms (for example, between the availability of various forms of transit and income), but their AIC and BIC values confirmed that the CNL model presented in this paper is preferred.

DISCUSSION AND CONCLUSIONS

In this chapter, we contrasted households who use public transit, Transportation Network Companies (TNCs; i.e., Uber and Lyft), and both by analyzing mode use data collected in the 2017 NHTS. We defined four mutually exclusive categories of households and estimated a Cross-Nested Logit model. To the best of our knowledge, this is the first nationwide study to contrast public transit and TNC users at the household level to understand the potential impact of TNCs on transit.

To stem the ridership decrease, transit agencies across the U.S. have been forming partnerships with Uber and Lyft to compensate for abandoned lines, address first and last-mile gaps, and offer service to night workers. For example, in 2016, San Clemente (in south Orange County, California) implemented a subsidized Lyft service to recapture some of the riders lost to the closure of two bus routes (191 and 193) (Swegles 2016). The goal was to provide on-demand service with special considerations for shopping trips for riders 60 and over. While the pandemic is partly responsible for the failure of this and similar initiatives in Southern California (Pho 2020), our results suggest that they were unlikely to succeed because Baby Boomers and Silent Generation households, as well as households with members with impaired mobility, are less likely to use TNCs, especially if they live in lower-density areas. Indeed, vehicles in use by TNCs typically are not equipped to accommodate customers with impaired mobility. Moreover, many older adults avoid such services because they are not comfortable using smartphones and because of discriminatory practices towards senior citizens by some TNC drivers (Williams 2021).

Our results show that transit and TNCs target households with common socio-economic characteristics and live in similar (relatively high density) areas. These households are more likely to have Millennials and post-Millennials, a higher income, advanced degrees, no children, and fewer vehicles than driver's license holders. They reside in denser areas and CBSAs served by public transit, and now TNCs. Compared to public transit, TNCs provide much more convenient and typically much faster point-to-point service that this group of households is likely to be able to afford, so increasing the exposure of these households to TNCs may hasten their exodus to TNCs.

Instead of outsourcing to TNCs, transit agencies should consider exploring partnerships with micro-mobility operators to extend the reach of transit and take care of the first- and last-mile problem. Multimodal connectivity with bike-sharing and micro-mobility has been adopted in countries around the world, but the U.S. is lagging (Mohiuddin 2021), even though these mobility options could potentially replace cars for up to 30% of trips under five miles, which make up more than half of all trips in the U.S. (Abduljabbar et al. 2021). Recent studies have shown that well-educated, younger adults, childless households, upper-income households, and urban dwellers with multiple mode options favor micro-mobility (Shaheen and Cohen 2019), so partnerships with transit where micro-mobility stations are conveniently located by public transit stops, and seamless payment options (such as apps integrating transit and micro-mobility) may help transit recover as it emerges from the pandemic. Embracing this approach may also enhance public health and help achieve GHG reduction goals.

Many low-income households (often belonging to minority and disadvantaged groups) also reside in core urban areas and CBSAs served by transit. However, we found that these households are less likely than higher-income groups to take both TNCs and public transit. The lower use of TNCs by less affluent households is unsurprising since it is typically not the cheapest transportation option. Extensive partnerships between transit and micro-mobility providers could prove attractive to them if pricing is right and micro-mobility stations are located in secure areas in minority neighborhoods. We note that African American and Asian households are also less likely to use TNCs (all else being equal), which suggests racial discrimination as uncovered in other studies (e.g., see Ge et al. 2016.

Our results also show that lower-income households are less likely to use public transit, which seems at odds with the disproportionate use of bus transit by lower-income households. The reason for this apparent discrepancy is that all households in our sample have access to at least one motor vehicle because the NHTS question analyzed in this paper was restricted to motorized households. Hence, none of the households we analyzed are fully captive as defined in the literature. Their disaffection for public transit reflects that transit lacks the convenience and the reach of private vehicles, as recent laws have made it easier for poorer emigrants to obtain driver's licenses. At the same time, some bus lines were discontinued, and bus frequency was reduced on many lines with shifts in transit investments from bus transit to commuter rail.

One limitation of this study is the restriction of our dataset (which comes from the 2017 NHTS) to households with at least one motor vehicle, which prevented us from analyzing carless households. A second limitation is the absence in the 2017 NHTS of detailed location data and of mode-specific data such as cost and travel time, which would have helped us better understand mode choice.

Future work could compare the travel behavior of similar households before and after the emergence of TNCs (using, for example, matching methods such as propensity score matching) and explore the potential opportunities and obstacles for transit to partner with micro-mobility providers.

REFERENCES

Abduljabbar, R.L., Liyanage, S., Dia, H. (2021). The role of micro-mobility in shaping sustainable cities: A systematic literature review. Transp. Res. Part D Transp. Environ. 92, 102734. https://doi.org/10.1016/j.trd.2021.102734

Alemi, F., Circella, G., Handy, S., Mokhtarian, P. (2018a). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. In: TRB 96th annual meeting. pp. 17-05630.

Alemi, F., Circella, G., Mokhtarian, P., Handy, S. (2018b). On-demand Ride Services in California: Investigating the Factors Affecting the Frequency of Use of Uber/Lyft. In: Transportation Research Board 97th Annual Meeting.

Alemi, F., Circella, G., Sperling, D. (2018). Adoption of Uber and Lyft, Factors Limiting and/or Encouraging Their Use and Impacts on Other Travel Modes among Millennials and Gen Xers in California. In: Transportation Research Board 97th Annual Meeting.

Blumenberg, E., Ralph, K., Smart, M., Taylor, B.D. (2016). Who knows about kids these days? Analyzing the determinants of youth and adult mobility in the U.S. between 1990 and 2009. Transp. Res. Part A Policy Pract. 93, 39–54. https://doi.org/10.1016/j.tra.2016.08.010

Brown, A.E., Blumenberg, E., Taylor, B.D., Ralph, K., Voulgaris, C.T. (2016). A taste for transit? Analyzing public transit use trends among youth. J. Public Transp. 19, 49–67. https://doi.org/10.5038/2375-0901.19.1.4

Buehler, R., Hamre, A. (2015). The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. Transportation (Amsterdam). 42, 1081–1101. https://doi.org/10.1007/s11116-014-9556-z

Chen, Z. (2015) Impact of ride-sourcing services on travel habits and transportation planning. 75.

Circella, G., Berliner, R., Lee, Y., Handy, S.L., Alemi, F., Tiedeman, K., Fulton, L., Mokhtarian, P.L. (2017). The Multimodal Behavior of Millennials: Exploring Differences in Travel Choices between Young Adults and Gen Xers in California. Transp. Res. Board 96th Annual. Meet.

Clark, H.M. (2017). Who rides public transportation? Washington D.C.: American Public Transportation Association.

Clewlow, R.R., Mishra, G.S. (2017). Shared mobility: Current adoption, use, and potential impacts on travel behavior. In: Transportation Research Board 96th Annual Meeting. pp. 9–10.

Erhardt, G.D., Roy, S., Cooper, D., Sana, B., Chen, M., Castiglione, J. (2019). Do transportation network companies decrease or increase congestion? Sci. Adv. 5. https://doi.org/10.1126/sciadv.aau2670

Ermagun, A., Levinson, D. (2017). Public transit, active travel, and the journey to school: a cross-nested logit analysis. Transp. A Transp. Sci. 13, 24–37. https://doi.org/10.1080/23249935.2016.1207723

Foth, N., Manaugh, K., El-Geneidy, A.M. (2013). Towards equitable transit: Examining transit accessibility and social need in Toronto, Canada, 1996-2006. J. Transp. Geogr. 29, 1–10. https://doi.org/10.1016/j.jtrangeo.2012.12.008

Garrett, M., Taylor, B. (1999). Reconsidering social equity in public transit. Berkeley Plan. J. 13, 6–27. https://doi.org/10.5070/bp313113028

Ge, Y., Knittel, C., MacKenzie, D., Zoepf, S. (2016). Racial and Gender Discrimination in Transportation Network Companies. Natl. Bur. Econ. Res. https://doi.org/10.3386/w22776

Grahn, R., Harper, C.D., Hendrickson, C., Qian, Z., Matthews, H.S. (2019). Socioeconomic and usage characteristics of transportation network company (TNC) riders. Transportation (Amsterdam). 47, 3047–3067. https://doi.org/10.1007/s11116-019-09989-3

Hall, J.D., Palsson, C., Price, J. (2018). Is Uber a substitute or complement for public transit? J. Urban Econ. 108, 36–50. https://doi.org/10.1016/j.jue.2018.09.003

Hampshire, R.C., Simek, C., Fabusuyi, T., Di, X., Chen, X. (2019). Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX Robert. Public Adm.

Harold M. Kohm (2000). Factors affecting Urban Transit Ridership. Bridging the Gaps. Canadian Transportation Research Forum, Proceedings of the 35th Annual Conference.

Hasnine, M.S., Lin, T.Y., Weiss, A., Habib, K.N. (2018). Determinants of travel mode choices of post-secondary students in a large metropolitan area: The case of the city of Toronto. J. Transp. Geogr. 70, 161–171. https://doi.org/10.1016/j.jtrangeo.2018.06.003

Henderson, P. (2017) Some Uber and Lyft riders are giving up their own cars: Reuters/Ipsos poll, https://www.reuters.com/article/us-autos-rideservices-poll/some-uber-and-lyft-riders-are-giving-up-their-own-cars-reuters-ipsos-poll-idUSKBN18L1DA.

Hunt, J. (2019). Canadian transit ridership continues to trend upwards, https://www.globenewswire.com/news-release/2019/11/13/1946490/0/en/Canadian-transit-ridership-continues-to-trend-upwards.html

Kim, S., Ulfarsson, G.F., Todd Hennessy, J. (2007). Analysis of light rail rider travel behavior: Impacts of individual, built environment, and crime characteristics on transit access. Transp. Res. Part A Policy Pract. 41, 511–522. https://doi.org/10.1016/j.tra.2006.11.001

Kooti, F., Djuric, N., Grbovic, M., Radosavljevic, V., Aiello, L.M., Lerman, K. (2017). Analyzing Uber's ride-sharing economy. In: 26th International World Wide Web Conference 2017, WWW 2017 Companion. pp. 574–582. Perth, Australia.

Krizek, K., El-Geneidy, A. (2007). Segmenting Preferences and Habits of Transit Users and Non-Users. J. Public Transp. 10, 71–94. https://doi.org/10.5038/2375-0901.10.3.5

LaChapelle, U. (2009). Transit Dependence and Choice Riders in the NHTS 2009: Associations with Walk, Bicycle and Transit Trips. 1–16.

Leistner, D.L., Steiner, R.L. (2017). Uber for seniors? Exploring transportation options for the future. Transp. Res. Rec. 2660, 22–29. https://doi.org/10.3141/2660-04

Malalgoda, N., Lim, S.H. (2019) Do transportation network companies reduce public transit use in the U.S.? Transp. Res. Part A Policy Pract. 130, 351–372. https://doi.org/10.1016/j.tra.2019.09.051

McDonald, N.C. (2015). Are millennials really the "go-Nowhere" Generation? J. Am. Plan. Assoc. 81, 90–103. https://doi.org/10.1080/01944363.2015.1057196

Mohiuddin, H. (2021) Planning for the first and last mile: A review of practices at selected transit agencies in the United States. Sustain. 13, 1–19. https://doi.org/10.3390/su13042222

Myers, D. (1997). Changes over time in transportation mode for journey to work: Effects of aging and immigration. Decenn. census data Transp. Plan. Case Stud. 2, 84–99.

Neff, J., Pham, L. (2007). A Profile of Public Transportation Passenger Demographics and Travel Characteristics Reported in On-Board Surveys. Washington, DC.

Pho, B. (2020). Orange County's Outsourcing of Public Transit to Lyft Nearly Left Residents Stranded, https://voiceofoc.org/2020/08/orange-countys-outsourcing-of-public-transit-to-lyft-nearly-left-residents-stranded/.

Polzin, S.E., Chu, X., Rey, J.R. (2000). Density and captivity in public transit success: Observations from the 1995 nationwide personal transportation study. Transp. Res. Rec. 10–18. https://doi.org/10.3141/1735-02

Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy. 45, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004

Rayle, L., Shaheen, S., Chan, N., Dai, D., Cervero, R. (2014). App-Based, On-Demand Ride Services: Comparing Taxi and Ridesourcing Trips and User Characteristics in San Francisco. Berkeley.

Sadowsky, N., Nelson, E. (2017) The Impact of Ride-Hailing Services on Public Transportation Use: A Discontinuity Regression Analysis. Econ. Dep. Work. Pap. Ser. 28.

Schaller, B. (2018). The New Automobility: Lyft, Uber, and the Future of American Cities. Brooklyn, NY 11215.

Shaheen, S., Chan, N., Bansal, A., Cohen, A. (2015). Shared Mobility. Definitions, Industry Developments, and Early Understanding. UC Berkeley.

Shaheen, S., Cohen, A. (2019). Shared Micromobility Policy Toolkit: Docked and Dockless Bike and Scooter Sharing.

Sikder, S. (2019) Who Uses Ride-Hailing Services in the United States? Transp. Res. Rec. 2673, 40–54. https://doi.org/10.1177/0361198119859302

Sperling, D. (2018). The Three Transportation Revolutions. Inst. Transp. Stud. Univ. California, Davis.

Swegles, F. (2016). San Clemente partners with Lyft to fill gaps after 2 OCTA bus routes end, https://www.ocregister.com/2016/10/05/san-clemente-partners-with-lyft-to-fill-gaps-after-2-octa-bus-routes-end/.

Taylor, B.D., Morris, E.A. (2015). Public transportation objectives and rider demographics: are transit's priorities poor public policy? Transportation (Amsterdam). 42, 347–367. https://doi.org/10.1007/s11116-014-9547-0

The Federal Highway Administration (2018). 2017 NHTS Data User Guide.

Train, K.E. (2009). Discrete choice methods with simulation, 2nd edition.

Vovsha, P. (1997). Application of cross-nested logit model to mode choice in Tel Aviv, Israel, metropolitan area. Transp. Res. Rec. 6–15. https://doi.org/10.3141/1607-02

Williams, D. (2021). After blind woman was denied rides more than a dozen times, https://www.cnn.com/2021/04/02/business/uber-blind-passenger-arbitration-trnd/index.html.

II. SHOULD TRANSIT BE MODELED AS AN ACTIVE MODE FOR COMMUTING? Evidence for California from the 2017 NHTS

INTRODUCTION

Physical inactivity and obesity among American adults have been recognized as an ongoing epidemic for quite some time (Gray et al., 2018; Ogden et al., 2014). For example, in 2011-2012, over one-third of American adults (34.9%) were obese (Ogden et al., 2014). Inactivity and obesity have been increasingly contributing to heart disease (Yatsuya et al., 2010), diabetes (Nguyen et al., 2011), and cancer (Jiao et al., 2010), so they have become one of the focal points of national health assessments (Ogden et al., 2014).

One approach to combat inactivity in daily life is to promote active transportation (walking and biking), so transportation planners have been advocating for additional pedestrian and biking infrastructure and more connections between active modes and transit stops (Kontou et al., 2020; Mohiuddin, 2021). Since transit riders either walk or bike to reach bus stops and transit stations, it can be argued that transit plays a quasi-active transport role and consequently helps promote physical activity. Several studies have shown that, compared to non-users, public transit users tend to walk and bike more (Besser & Dannenberg, 2005; Bopp et al., 2015; Lachapelle & Frank, 2009; MacDonald et al., 2010). However, the transportation literature typically considers public transit as a non-active mode when evaluating its association with physical health benefits (Lachapelle et al., 2011; Lachapelle & Frank, 2009; MacDonald et al., 2010) even though it requires some level of physical activity.

In this context, we explore whether public transportation should be grouped with both active and non-active modes when analyzing travel attributes instead of being treated as an inactive mode. For that purpose, we constructed a cross-nested logit (CNL) structure based on three modes commonly used to commute to work (private vehicles, public transit, and walking/biking) and compared it statistically with a nested logit and a simple multinomial logit model. Our two-level CNL structure considers public transit an overlapping alternative (second level) that shares utility with both active and non-active modes in the first level. We then called public transit a "pseudo active mode" while deriving its utility from the active transport nest. We estimated our models using California data from the 2017 NHTS. Beyond the modeling interest of this exercise, if this approach is valid, it could provide arguments for public investments in facilities around transit stops (Kontou et al., 2020; Mohiuddin, 2021). To the best of our knowledge, no published U.S. study has yet explored the extent to which public transit shares utility with walking and biking in a discrete choice framework.

After reviewing selected papers dealing with active transportation and public transit, we present our data before motivating our modeling approach. We then discuss our results, summarize our conclusions, mention some limitations of our work, and suggest some ideas for future research.

LITERATURE REVIEW

Part of the motivation for this chapter comes from two studies that estimated CNL models to investigate if public transit could be partly modeled as an active mode. The first one is due to Ermagun & Levinson (2017), who developed a CNL model where they considered public transit a combined travel mode. After estimating their CNL model on a sample of 3,441 students in Tehran, they showed that a 1% increase in the distance between home and school reduces physical activity by 0.91%, which would jump to 2.2% if transit is not considered a combined mode. The second study is due to Bekhor & Shiftan (2010), who were interested in the factors that drive people to shift from private cars to alternatives such as temporary pick-up and drop-off zones. Instead of considering these two alternatives as a single nest, they combined them with public transportation and private cars. Their comparison between MNL, NL, CNL, and kernel logit models shows that CNL outperforms other structures (Bekhor & Shiftan, 2010).

Our second motivation is the linkage between transportation and health. Understanding the association between public transit as a commuting mode (both to work and school) and physical activity has long been of interest to transportation researchers (e.g., see Lachapelle et al., 2011; Lachapelle & Frank, 2009; MacDonald et al., 2010).

Many of these studies we found were conducted in the United States. For example, Besser & Dannenberg (2005) extracted the data of 3,312 transit users from the 2001 NHTS and showed that 29% of public transit users achieve more than 30 minutes of daily physical activity by walking to and from transit. Similarly, after estimating a Tobit model on 2001 NHTS data for 28,771 persons, Edwards (2008) concluded that transit users add 8 to 10 min of physical activity daily simply by walking to and from transit stops. Lachapelle & Frank (2009) also found a positive correlation between public transit, walking, and moderate physical activity in metropolitan Atlanta, Georgia.

MacDonald et al. (2010) explored the impact of light rail transit (LRT) use on body mass index (BMI) and physical activity in North Carolina. They found that LRT use is directly associated with increased physical activity and an average BMI reduction of 1.18 points.

In the Baltimore, MD, and Seattle, WA, metropolitan areas, Lachapelle et al. (2011) correlated block-level walkability index, income, moderate-intensity physical activity (MPA), and frequency of transit commuting. They reported that transit users achieve approximately 5 to 10 minutes more MPA than non-users regardless of neighborhood walkability (Lachapelle et al., 2011).

This topic has also been of interest abroad. For example, Batista Ferrer et al. (2018) showed that people who walk or take transit to work are more physically active than car users based on data collected from urban workplaces in southwest England and South Wales.

To conclude this brief review, let us mention that a growing literature is analyzing the use of public transit to transport children to and from school, and the health benefits of keeping children physically active (Ermagun, Hossein Rashidi, et al., 2015; Ermagun, Rashidi, et al., 2015; Ermagun & Levinson, 2017a; Ermagun & Samimi, 2015, 2016; Owen et al., 2012; Pabayo et al., 2012; Voss et al., 2015). Table **II-1** summarizes the studies discussed in this section.

Table II-1: Summary of Selected Studies

Authors (year)	Data source and methodology	Variables	Key findings
Batista Ferrer et al. (2018)	• 654 employees in 87 workplaces in urban areas of the southwest of England and South Wales. • May-July 2015, and March-May 2016 • Accelerometers, Global Positioning System (GPS) receivers, travel diaries, and questionnaires. • Multivariate logit	• Gender, age, annual household income, education, weight status, occupation, commute distance, commute time, time spent on moderate to vigorous daily physical activity • Alternatives: driving, walking, and public transport modes to work	• There are strong correlations between walking, public transport mode to work, and physical activity • Walkers and public transit users accrue daily 34.3 and 25.7 minutes of moderate to vigorous physical activity; car users only spend 7.3 minutes walking.
MacDonald et al. (2010)	• 498 adult household members interviewed to identify the effect of light rail transit (LRT) use on BMI, obesity, and weekly recommended physical activity in Charlotte, NC • July 2006– February 2007 (before the construction of LRT), and March 2008–July 2008 (after the construction of LRT) • Multivariate regressions	• Age, gender, race, employment status; education level, homeownership, distance to work, perceptions of neighborhood environments, access to parks, density of food and alcohol establishments; household density • Weekly use of public transit to commute to work	• LRT use reduced BMI by 1.18 and obesity by 81%; if the physical environment to access LRT could be improved, people's physical health would improve too.
Lachapelle et al. (2011)	• 1237 adults aged between 20 and 65 from 32 neighborhoods in Seattle and Baltimore in 2003 • Hierarchical Linear Regression and Chi-square tests	• Percentage of commute trips by public transit (bus, subway, and trolley); walking and biking trips; age, gender, marital status, race, Hispanic status, income, number of vehicles in the household (HH); psychosocial measure; walkability index; neighborhood income status	• Transit users accumulated 4 (infrequent) to 8 (frequent) more minutes of measured moderate physical activity per day than non-transit users • Significant differences for walking trips were observed between transit and non-transit users in low walkability neighborhoods. In high walkability neighborhoods, non-transit commuters walked as frequently to all other destinations as transit commuters

Lachapelle & Frank (2009)	• Data from 4,156 respondents from the 2001–2002 SMARTRAQ travel survey in metropolitan Atlanta, Georgia, to evaluate the correlation between walking for transit and physical activity • Multinomial logit	• *Dependent variable:* No measured walking, moderate walking (mean walk distance <2.4 km), and sufficient walking (mean walking distance >=2.4 km) • *Independent variable:* Age, race, income, gender, car availability; types of employer-sponsored transit passes, residential density (res. units/net res. acre); retail stores within 10-min walk from work, neighborhood density, distance to nearest transit stop; mean number of public transit trips, trips as driver and trips as passenger per day	• Walking to transit helps achieve recommended levels of physical activity • Those who used employer-sponsored transit passes tend to walk more than non-walkers and moderate walkers • Low-income people, who must rely on transit and own a smaller number of private vehicles, also meet the recommended physical activity target
Owen et al. (2012)	• 2,035 white European, South Asian, and Black African-Caribbean origin children (aged 9–10 years) in the UK who studied in 2006 and 2007 • Physical activity monitored during school hours: 8 to 9 am and 3 to 5 pm on a weekday • Multilevel linear regression	• School modes: walking/cycling, public transport (bus/train), and car for weekdays and weekends. • Outcome variables: activity counts, activity counts per minute, counts per minute (CPM), and time spent in different levels of activity (sedentary, light, moderate, vigorous, moderate to vigorous physical activity (MVPA) • Covariates: Gender, Ethnic group, distance from school,	• Children who use active modes to school (walking, biking, and public transit) are more physically active than those who use private cars. • Caucasian and multi-ethnic children, who walk or cycle to school, accumulate 8 and 7 minutes more MVPA, respectively, than their counterparts driven to school. • Children who use public transit either have a similar or higher level of physical activity, compared to children who walk and bike to school
Pabayo et al. (2012)	• 688 grade 5 children of Alberta, Canada in 2009 • Two-tailed t-tests, multilevel multiple linear regression	• Modes: active transports-- city bus, walks/bikes; non-active transport: school bus, drive, or other. • Pedometer reading of children's physical activity: number of steps/hour • Cofounders: birthplace, level of education, household income, child's age, gender, weight.	• Children who walk to school are more physically active throughout most of the day (after school and evening) than those driven in cars

Voss et al. (2015)	• 49 high school students from Downtown Vancouver • Active Streets, Active People–Junior study, collected in October 2012	• Primary mode: walk, car and transit • Trip duration, distance, speed, and trip-moderate-to-vigorous physical activity • Age, BMI, weight, distance to school, home location within school catchment area, physical activity (CPM/day), MVPA,	• Students who use transit or walk to school cover a similar distance • Students accumulate ~9 min of moderate to vigorous physical activity during a school trip
Kontou et al. (2020)	• 30,064 children and adolescents between 5 to 17 years old. • 2017 NHTS • Descriptive statistics and binary logit model	• *Dependent variable:* active travel mode to school vs. no active travel mode • *Independent variable:* distance to school, minutes to school, grade level, gender, race, HH vehicle ownership, homeownership, population density.	• Less than 10% of children walk to school; ~1.1% bike to school. • 75% of walking trips to school are <1 mile; biking trips are typically 0.5 to 1 mile
Edwards (2008)	• 28,771 adults (>=18 years old) of the entire US • 2001 NHTS • OLS and Tobit model	• *Dependent variable:* total daily walking time, total daily biking time • *Explanatory variable:* age, gender, race, Hispanic status, education, household income, homeownership, census division of residence, population density, MSA status, number of HH vehicles, walking status, transit use status	• An adult can save US$5500 in medical expenses through increased physical activity • A net expenditure of 100 kcal/day can reduce obesity.
Ermagun & Levinson (2017)	• Cross-sectional survey of 4,700 middle and high school students in Tehran in 2011 • MNL, NL and CNL	• *Explanatory variables:* Gender age, income, parent's work status, education of parents, travel cost for school service, car travel cost, distance between home and nearest bus stops, population density, walking time to school, safety and reliability of school travel, traffic zones • *Modes:* walking, public transit, private car, and school service	• If the distance between home and the workplace increases by 1%, the probability of walking decreases by 3.5% and public transit use by 1.0% • Physical activity decreases by 0.9% if the distance from home to school increases by 1%
Bekhor & Shiftan (2010)	• Stated Preference survey of 3,588 work trips in Tel Aviv • MNL, NL, CNL, and Logit Kernel Model	• *Modes:* Bus with walking, kiss-and-ride, park-and-ride; rail with walking, bus access, car driver and car Passenger • *Explanatory variables:* access and walking time plus costs (incl. parking when appropriate) for each mode.	• Park and ride, a combined transportation mode, should be put in a CNL structure to avoid model misspecification.

DATA

In this chapter, we analyzed data from the 2017 NHTS, which collected extensive socio-economic and travel information from 129,969 households using a stratified sampling approach. The resulting dataset is organized into four files: person, household, vehicle, and trip files (U.S. Department of Transportation, 2018).

Dependent Variable

Our dependent variable is the actual mode to work on the day of the 2017 NHTS, which we extracted from the trip file of the 2017 NHTS. Panel A of Figure II.1 shows the modes reported by Californians for going to work in the 2017 NHTS, with no fewer than 20 different modes for 9,701 observations). After excluding unconventional commuting modes (124 observations) such as golf carts/Segways, motorcycles/mopeds, recreational vans (RV), city-to-city buses (Greyhound, Megabus), airplanes, boats/ferries/water-taxis, as well as taxis and TNCs (Uber, Lyft, UberPool, etc.), we collapsed the remaining work modes (9,577 observations) into three broad alternatives (Panel B of Figure II.1):

- Alternative 1 - Private vehicles: Car, SUV, Van, Pickup truck
- Alternative 2 - Public transit: school bus, public or commuter bus, paratransit/dial-a-ride, shuttle bus, Amtrak/commuter rail, and subway/elevated/light rail/streetcar
- Alternative 3 - Walk and bike

Explanatory Variables

We selected our explanatory variables based on our literature review and the variables available in the 2017 NHTS dataset. We divided our explanatory variables into four broad categories: alternative-specific variables, individual-specific variables, household-specific variables, and land-use variables. We first processed alternative specific variables (commuting distance and time) before merging these variables with our socio-economic (individual and household-specific characteristics) and land-use variables.

Alternative specific variables

Commuting distance and time on the survey day are our primary alternative specific variables in this study. Since survey data can only provide travel time for one mode (the one used on the survey day), we estimated travel time and distance for driving, transit, and biking for the survey day via GEOROUTE in Stata. Travel distance also varies between modes. For transit, it reflects those commuters who are traveling along transit lines, which are not necessarily the shortest network distance between two points. Moreover, bikers may be able to use paths that are unavailable to private motor vehicles. We extracted commuters travel day commuting information from the trip file of the 2017 NHTS and provided GEOROUTE with the day and the time of each trip in addition to its origin and destination (longitude and latitude) and asked for travel distance and travel time for each of the three modes we are considering (driving, transit, and biking/walking). When a commuter traveled more than once to her/his work location, we kept only the first one. This gave us commuting data for three modes for 9,082 commuters.

To consider only “practical” commuting distances and durations, we dropped observations for which the commuting distance was above 50 miles, and commuting duration was over 90 minutes for any of the three modes considered. Panels A-B of Figure II.2 show the distributions of commuting distances and times after this step. After removing observations for which we did not have complete information for all three modes considered, our final sample has commuting information for 3,079 workers.

Individual specific variables

We gathered the following information from the person file: age, gender, race, Hispanic status, education, and whether someone was born abroad.

Some studies have considered age and gender for explaining individual travel preferences (Lachapelle & Frank, 2009; MacDonald et al., 2010; McDonald, 2015). We dropped individuals under 16 years old to conform with the working-age limit in California.

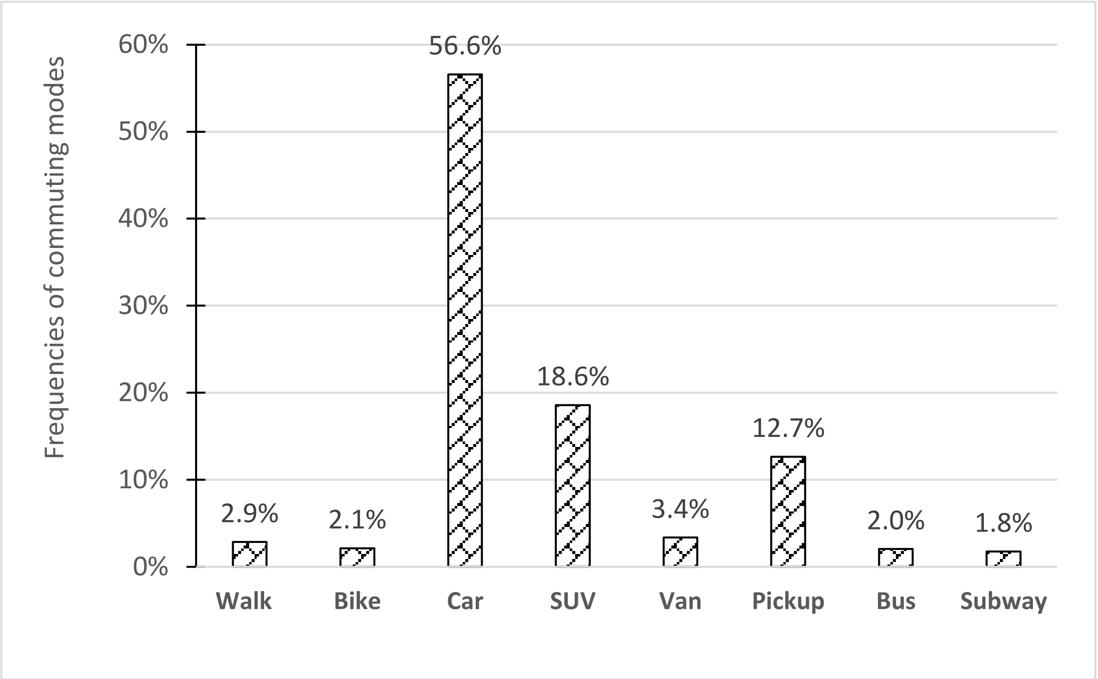
We also know that race and Hispanic status may matter for selecting a mode (Buehler & Hamre, 2015). Based on the frequency of responses in the 2017 NHTS, we defined four binary race variables: Caucasian, African American, Asian, and Others. In our sample, a binary race variable equals one if that individual identifies as belonging to that race and zero otherwise. The "others" category captures the remaining groups, including American Indian, Alaska Native, Native Hawaiian, other Pacific Islander, multiple responses, or some other race. Hispanic status was defined similarly. We also created a binary variable for people not born in the U.S.

The literature suggests that education plays a pivotal role in commuting mode choice (Buehler & Hamre, 2015; McDonald, 2015). To capture the level of education of a commuter, we created four binary variables: less than high school and high school or GED, some college or associate degree, BS/BA, and graduate or professional.

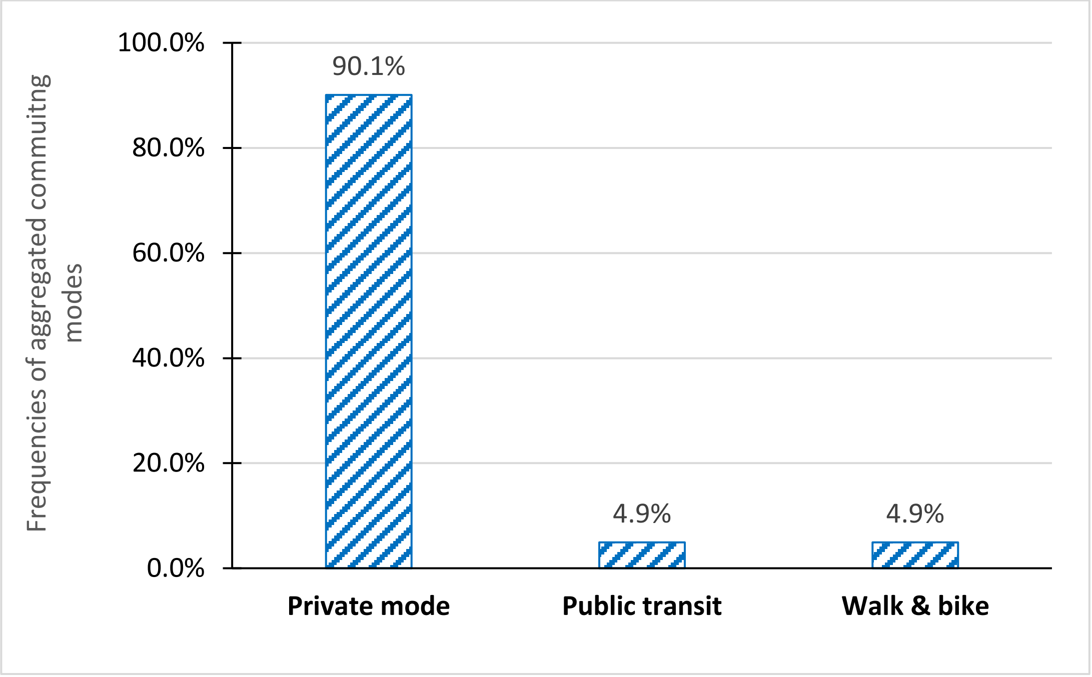
Household variables

We also used household-specific variables in our models: annual income, number of drivers and vehicles, number of people in the household, and homeownership. For income, we collapsed the eleven categories in the 2017 NHTS into six binary categories to represent annual household income, as shown in Table **II-2**. Likewise, homeownership is captured by a binary variable and household size as a continuous variable.

As the decision to take any modes other than an individuals' private vehicle should not depend directly on the number of household vehicles or the number of driver's license holders, but rather on whether a household has more drivers than vehicles, we created a binary variable that equals one if a household has more drivers than vehicles and 0 otherwise.

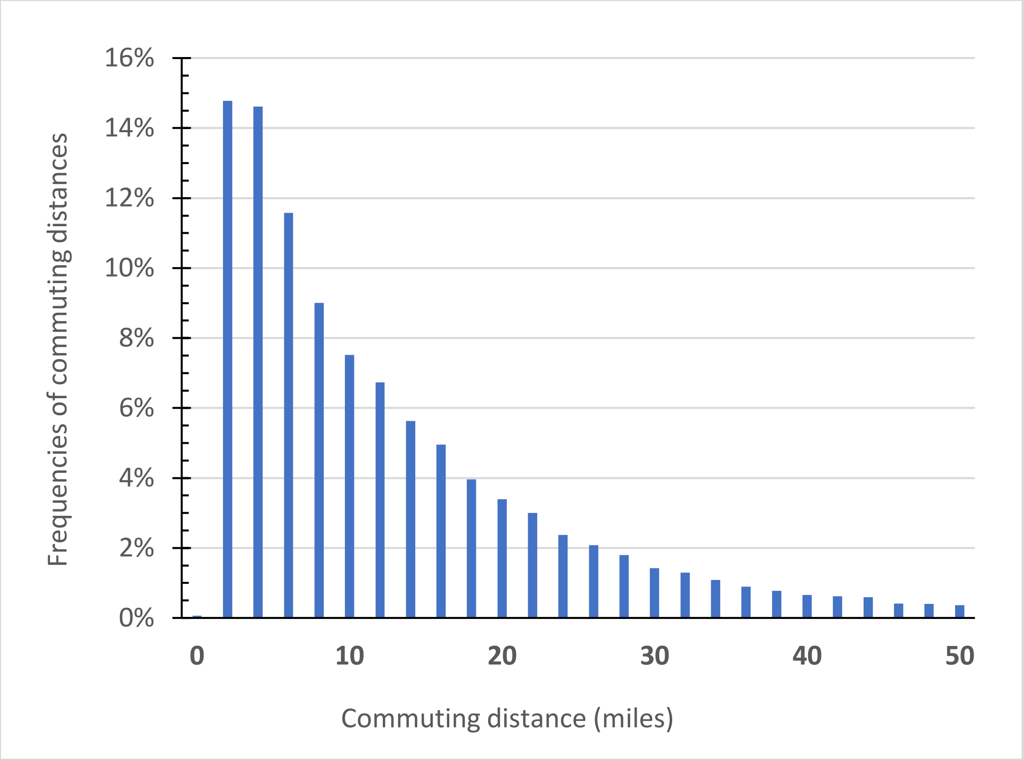


Panel A: Frequencies of commuting modes (Source: 2017 NHTS)

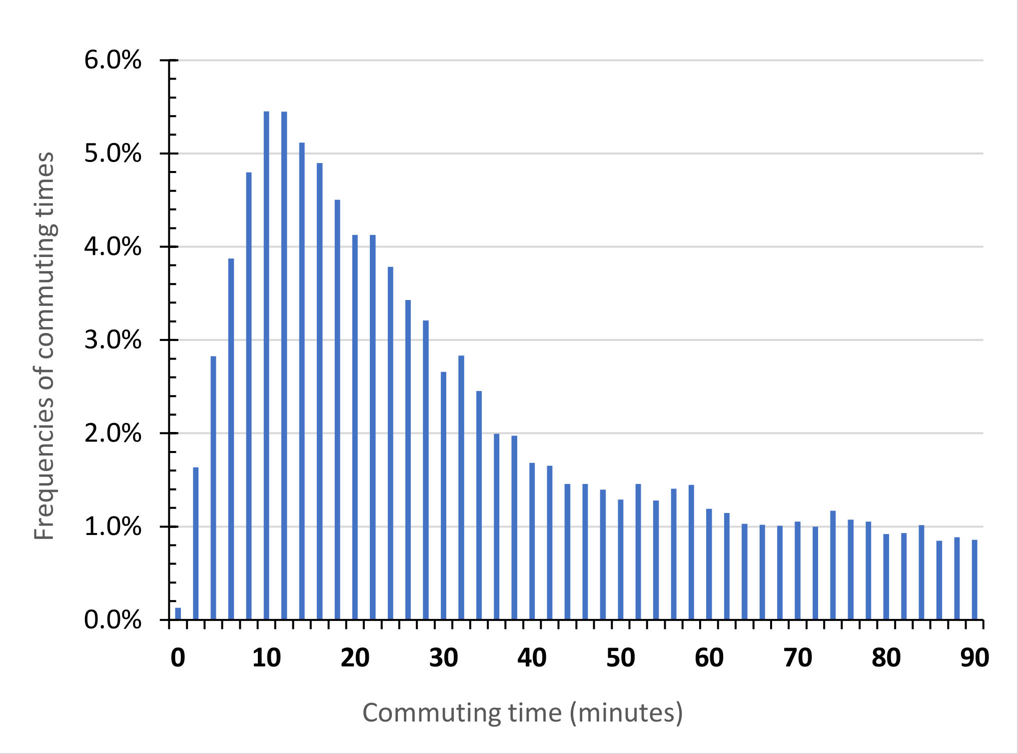


Panel B: Frequencies of aggregated commuting modes in our sample

Figure II.1. Characterization of commuting modes



Panel A: Distribution of commute distance (after discarding values > 50 mi)



Panel B: Distribution of commute time (after discarding values > 90 min)

Figure II.2. Commuting characteristics

Table II-2. Descriptive Statistics (N = 3,030)

	Mean	Std. Dev.	Min	Max
Travel attributes				
Commute distance by private cars (mi)	3.81	3.03	0.00	16.60
Commute time by private cars (min)	9.53	5.46	0.00	30.00
Commute distance by public transport (mi)	4.24	3.36	0.00	23.46
Commute time by public transport (min)	50.72	23.96	0.00	90.00
Commute distance by walk and bike (mi)	3.48	2.73	0.00	13.52
Commute time by walk and bike (min)	26.37	20.31	0.00	89.75
Individual attributes				
Age	44.59	14.81	16.00	89.00
Gender (Male=1)	0.47	0.50	0.00	1.00
Hispanic Status (Hispanic =1)	0.18	0.39	0.00	1.00
Ethnicity				
Caucasian	0.71	0.45	0.00	1.00
African American	0.13	0.34	0.00	1.00
Asian	0.03	0.18	0.00	1.00
Others	0.12	0.33	0.00	1.00
Educational attainment				
Less than high school and high school degree	0.16	0.37	0.00	1.00
Some college degrees	0.28	0.45	0.00	1.00
Undergraduate degree	0.28	0.45	0.00	1.00
Graduate or professional degree	0.27	0.45	0.00	1.00
Immigration Status				
Commuter was born outside the U.S.	0.21	0.41	0.00	1.00
Household attributes				
Annual household income				
<$25,000	0.10	0.29	0.00	1.00
$25,000 to $49,999	0.19	0.39	0.00	1.00
$50,000 to $74,999	0.17	0.37	0.00	1.00
$75,000 to $99,999	0.14	0.35	0.00	1.00
$100,000 to $149,999	0.22	0.41	0.00	1.00
>=$150,000	0.18	0.39	0.00	1.00
Number of people in the household	2.56	1.34	1.00	10.00
Household homeownership (Yes=1)	0.57	0.50	0.00	1.00
Household drivers and vehicles				
Household has fewer vehicles than drivers	0.13	0.34	0.00	1.00
Land use attributes				
Population density (1000 persons/sq. miles)	9.53	7.79	0.05	30.00
MSA population with access to rail				
Household lives in MSA over one million with rail	0.39	0.49	0.00	1.00
Household lives in MSA over one million without rail	0.24	0.43	0.00	1.00
Household lives in an MSA under 1 million	0.28	0.45	0.00	1.00
Household does not live in an MSA	0.09	0.29	0.00	1.00
Number of transit-stops within 500 m of home	7.18	8.66	1.00	91.00
Number of transit-stops within 500 m of workplace	12.06	16.58	1.00	131.00

1. Our study has three alternatives: i) Private mode to work: 2,454; ii) Public Transit mode to work: 206; and iii) Walking & biking to work: 370
2. For a binary 0/1 variable, the mean is the fraction of the sample for which it equals 1.

Land use variables

It is well-known that land use influences mode choice (Buehler & Hamre, 2015; Timperio et al., 2018). Therefore, we included in our models two of the most common land-use variables from the 2017 NHTS: population density (1,000 persons/sq. mile) of the residential census tract of households in our sample, and characteristics of the metropolitan statistical area (MSA) where they reside (over 1million people with heavy rail, over 1 million people without heavy rail, under 1 million, and not in MSA). The latter was included as binary variables with residence not inside an MSA serving as our baseline.

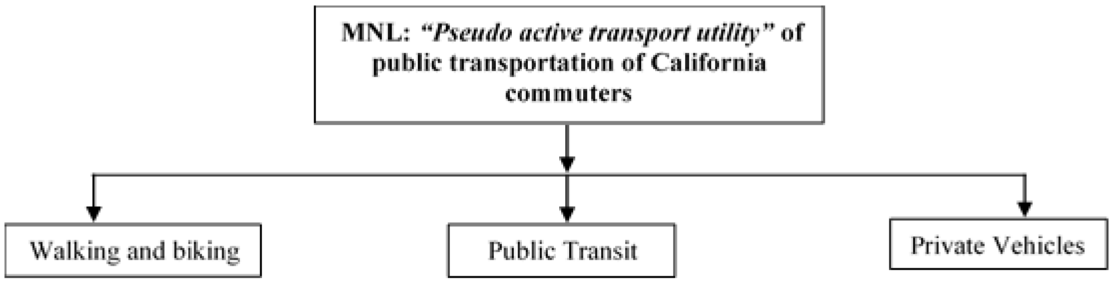
Our literature review also showed that places with more dynamic transit facilities, such as transit stops within walking distance, increase riders' tendency to walk to get on public transit. We, therefore, incorporated the following two variables in our models: the number of transit stops within 500 m of a commuter's home, and the number of transit stops within 500 m of a commuter's workplace. To create these two variables, we first gathered location (longitude and latitude) information about the transit stops for the 141 available transit agencies in California from the General Transit Feed Specification (GTFS) website and combined them with the home and workplace locations (longitude and latitude) of each commuter in our sample using ArcGIS.

After merging the alternative specific attributes described above with the individual, household, and land use attributes, our final sample has information on three modes for 3,030 workers (for a total of 9,090 observations). Table **II-2** presents descriptive statistics for the explanatory variables used in our models.

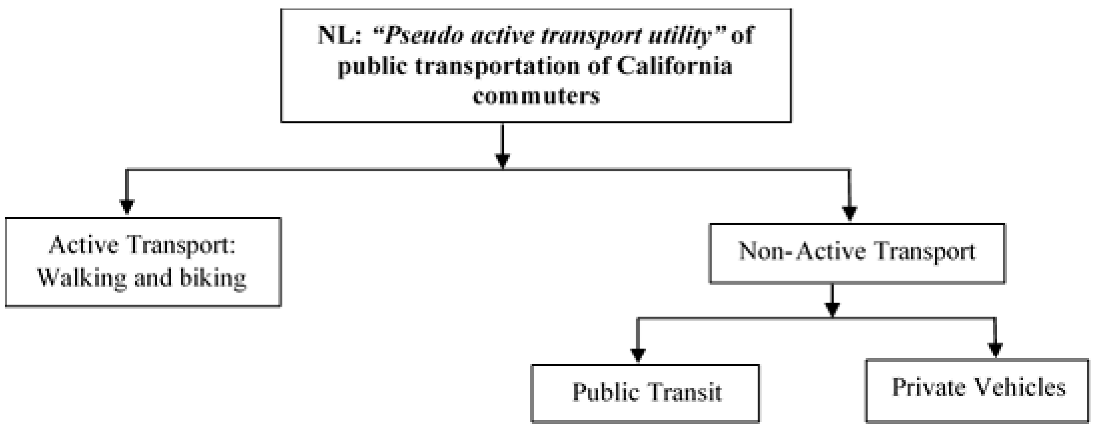
MODELS

We estimated three models. For simplicity, we started with a Multinomial Logit (MNL) model. This model implies the Independence of Irrelevant Alternatives (IIA; see Train, 2009), which requires errors to be uncorrelated. The nested logit (NL) model relaxes the IIA requirement by allowing alternatives in the same nest to have correlated errors (Train, 2009). However, a Cross Nested Logit (CNL), which has been used numerous times for analyzing mode choice (Bekhor & Shiftan, 2010; Ermagun & Levinson, 2017; Hasnine et al., 2018; Vovsha, 1997), appears more suitable here to test our hypothesis of an overlap of "Public transportation" in the "Active Transport" and "Non-active Transport" nests. The structures of our MNL, NL and CNL models are presented in Panels A-C of Figure II.3.

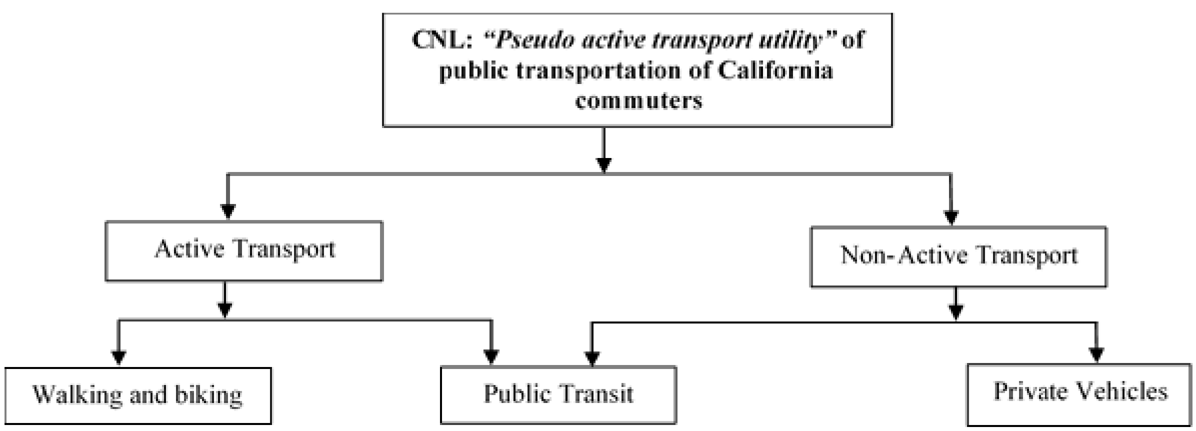
In a CNL model with nests B_1, B_2, … $B_{.K.}$, an alternative can belong to more than one nest (Train, 2009). The extent to which alternative *j* belongs to nest *k* is given by the allocation parameter, denoted by $\alpha_{jk}\geq 0$. Allocation parameters are non-negative, and they sum to one over nests for a given alternative, i.e., $\sum_k \alpha_{jk} = 1$ so that allocation parameter α_{jk} reflects the percentage by which alternative *j* belongs to nest *k* (α_{jk}=0 indicates that alternative *j* does not belong in nest *k*) (Train, 2009).



Panel A: Multinomial Logit Structure



Panel B: Nested Logit Structure



Panel C: Cross Nested Logit Structure

Figure II.3. MNL, NL, and CNL model structures

The second type of parameters (log-sum parameters) type plays an essential role in characterizing nests in a CNL model. They were denoted by $\lambda_k \geq 0$). The log-sum parameter for nest *k* reflects the degree of independence among alternatives within nest *k*, with a more significant value indicating greater autonomy and less correlation. Values of log-sum parameters between 0 and 1 guarantee consistency with utility maximization, but consistency with utility maximization may still hold for a range of alternatives when log-sum values are above one (Train, 2009).

A choice model is defined by the expression of the probability that decision-maker *n* selects alternative *i*. For the CNL, this expression is given by (Train, 2009):

$$P_{ni} = \frac{\sum_k (\alpha_{ik} e^{V_{ni}})^{1/\lambda_k} \left(\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} (\alpha_{jl} e^{V_{nj}})^{1/\lambda_l} \right)^{\lambda_l}} \tag{1}$$

If each alternative enters only one nest, the α_{jk} parameters are 0 or 1, and the CNL simplifies to the nested logit model. More specifically, for a CNL, the probability that person *n* is in category *i* can also be written (Train, 2009):

$$P_{ni} = \sum_k P_{ni|B_k} * P_{nk} \tag{2}$$

where the probability that person *n* falls in nest *k* is:

$$P_{nk} = \frac{\left(\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k} \right)^{\lambda_k}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} (\alpha_{jl} e^{V_{nj}})^{1/\lambda_l} \right)^{\lambda_l}} \tag{3}$$

and the probability that person *n* selects *i* given that (s)he is in nest *k* is:

$$P_{ni|B_k} = \frac{(\alpha_{ik} e^{V_{ni}})^{1/\lambda_k}}{\sum_{j \in B_k} (\alpha_{jk} e^{V_{nj}})^{1/\lambda_k}} \tag{4}$$

We estimated unknown model parameters via maximum likelihood in Stata.

RESULTS

We estimated our models using Stata 15 and BisonBiogeme (Version 2.6a) (Bierlaire, 2020). A check for multicollinearity showed that it is not an issue here since the maximum VIF value is <7.0. Although our nested logit model has lower AIC and BIC values, its logsum parameter is over 1, so we did not consider it further. Our best model here is our multinomial logit model (MNL) because it has lower AIC and BIC values, and the IIA assumption, which is critical for MNL models, is not violated.

Results are shown in Table **II-3**. It displays exponentiated model coefficients, which are odds ratios (OR) for the MNL model (Hosmer & Lemeshow, 1991). The odd of an event is the ratio of the probability that the event will happen (here that a commuter will pick a specific mode for commuting) divided by the probability that it will not occur, calculated using the explanatory variables in the logit model. In the odds ratio for explanatory variable *j*, the odds in the denominator are calculated with the same explanatory variable values as the odds in the denominator, except that explanatory variable *j* is larger by one unit. If the OR for explanatory variable *j* is around 1 for a commuting mode (driving, transit, and walk and bike), then explanatory variable *j* has no impact on whether a commuter will choose that mode; if the OR is greater than one, a commuter is more likely to take that mode for commuting; the reverse holds if OR is lower than one. Note, however, that this interpretation does NOT hold for NL and CNL models. Our discussion focuses on results for the MNL model.

We specified actual travel distance and travel time as generic coefficients in our model. Results for commuting distance (1.32**) and time (0.95***) suggest that commuters are more sensitive to time than to distance. Longer travel time by walking and biking or public transit is one of the reasons that commuters prefer to drive to work (Frank et al., 2008; Clark, 2017).

Let us now discuss estimated coefficients for individual-specific variables (socio-economic and household attributes of commuters).

First, we found that men favor walking and cycling (1.90***) more than women while traveling to work (Brown et al., 2016). In our MNL model, age, Hispanic status, and race do not play a significant role.

Education matters but only for advanced degree holders. Our results show that commuters with a graduate degree (1.52*) are more inclined to walk and bike to work than to drive or to use public transit, as also reported by Clark (2017). We also found that knowing whether a commuter was born in the U.S. is not informative about her/his mode to go to work.

Several household variables are statistically significant. First, a large family would not prefer active transport (0.85*) to go to work. Similarly, if a person owns a home, they would be less prone to walk and bike or ride public transit and more into private cars. But if a household holds fewer vehicles than driving licenses, they are more prone to use any other available options, such as walk and bike (4.71***) or public transit (4.19***).

Geographical variation plays a significant role in commuter' mode choice to work. Our land-use variables echoed the findings of other literature. For example, in a populated area, people would use public transit (1.03***) instead of private cars (although this effect is small). Similarly, workers living inside a densely populated MSA area, with or without rail services, would be much more likely to take public transit use but not active transport modes. One probable reason could be inadequate and insufficient pedestrian and bike facilities (Turrell et al., 2013). Transit stops variables substantiate this finding. Indeed, riders living in an area with transit stops within 500-meter walking from home and work would prefer both walking and biking or public transit over driving (Renne et al., 2016). This is an important finding of our model.

Table II-3. MNL, NL, and CNL Results (N=3,030)

	Baseline = Private vehicle (N=2,454)					
	MNL		NL		CNL	
	Public Transit (N=206)	Walking and Biking (N= 370)	Public Transit (N=206)	Walking and Biking (N= 370)	Public Transit (N=206)	Walking and Biking (N= 370)
Travel attributes						
Commute distance in miles	1.32***		1.56**		1.35***	
Commute time in minutes	0.95***		0.89***		0.95***	
Individual attributes						
Age	0.99	0.99	0.97	0.99	0.99**	0.99
Gender (Male=1)	1.20	1.93***	1.64	2.12***	1.46***	1.77***
Hispanic Status (Hispanic =1)	1.13	0.73	1.64	0.77	1.11	0.75
Ethnicity (base = Caucasian)						
African American	1.55	0.86	7.08*	1.03	1.43	0.90
Asian	1.42	0.87	1.71	0.87	1.49	0.86
Others	1.38	1.34	3.49	1.59*	1.40	1.33
Educational attainment (base = Undergraduate degree)						
Less than high school or High school degree	1.74	1.37	1.60	1.36	1.59*	1.43*
Some college degrees	0.99	0.78	0.32	0.71	0.88	0.83
Graduate or professional degree	1.48	1.52*	3.29	1.76**	1.54**	1.51***
Immigration Status						
Commuter was born outside US	0.75	0.77	0.22*	0.63*	0.72*	0.80
Household attributes						
Annual household income (base= $50,000 to $74,999)						
<$25,000	1.36	1.24	2.18	1.31	1.24	1.26
$25,000 to $49,999	0.86	0.74	0.71	0.68	0.77	0.77
$75,000 to $99,999	0.52	0.81	0.29	0.80	0.57**	0.77
$100,000 to $149,999	0.67	1.04	0.30	0.98	0.73	1.00
>=$150,000	0.72	0.96	0.24	0.85	0.71	0.95
Number of people in the household	0.87	0.85**	0.70	0.84**	0.85***	0.87***
Household home ownership (Yes=1)	0.57**	0.60***	0.21*	0.56***	0.62***	0.57***
Household drivers and vehicles						
Household has fewer vehicles than driver	4.71***	4.19***	20.55***	5.31***	4.76***	4.10***
Land use attributes						
Population density (1000 persons/sq. miles)	1.03*	1.00	1.15***	1.02	1.02*	1.01

MSA population with access to rail (base = HH does not live in an MSA)						
Household lives in MSA over one million with rail	3.31*	0.63	25.30	0.97	2.77**	0.73
Household lives in MSA over one million without rail	2.74*	0.76	11.78	1.04	3.16**	0.62**
Household lives in an MSA under 1 million	1.16	0.83	0.52	0.92	1.24	0.81
Number of transit-stops within 500 m of home	1.03**	1.06***	1.05	1.06***	1.04***	1.06***
Number of transit-stops within 500 m of workplace	1.05***	1.02***	1.13***	1.04***	1.04***	1.03***
Log-sum parameters						
Active Transportation nest	NA		1 (Fixed)		0.14***	
Non-Active Transportation nest	NA		3.839***		1.00	
Allocation Parameters						
Active Transportation nest	NA		NA		0.369***	
Non-Active Transportation nest	NA		NA		0.631***	
Log-likelihood at convergence	-1359.96		-1318.26		-1359.96	
AIC	2823.90		2744.50		2839.91	
BIC	3193.90		3128.70		3200.89	

Notes:

1. * p<0.05, ** p<0.01, *** p<0.001.

2. This table presents exponentiated estimated coefficients, which are odds ratios (OR) for our MNL model but not for the other models. An odds ratio (OR) greater than 1 for a specific variable of a particular alternative indicates an increased likelihood towards that alternative compared to the corresponding baseline, and a value less than 1 indicates the reverse. An OR close to one indicates little practical impact.

CONCLUSIONS

This chapter explored whether public transit should be treated as a *"pseudo active transport"* that shares utility with active modes while modeling mode choice in a discrete choice modeling context. We compared three models (multinomial logit, nested logit, and cross-nested logit) and controlled for a broad range of socio-economic, demographic, and geographic variables known to influence mode choice for commuting. We found that our simplest model (a multinomial logit model, MNL) out-performs the other two and that, for our dataset, taking transit is best modeled separately (it should not be grouped with walking and biking in a nesting structure). We also checked that the IIA assumption, which is critical for MNL models, is not violated.

Our findings highlight the importance of travel time between home and workplace. Moreover, we found that insufficient walking and biking facilities will refrain commuters from using these modes even in more compact and denser areas. This clearly shows the importance of developing more walking and biking infrastructure in urban areas in California.

One limitation of our study is that the HERE website does not have actual transit schedules before 2020, so transit travel times (travel in the 2017 NHTS took place in 2016 and 2017) do not reflect actual transit schedules. Future work could re-estimate our models with additional land-use variables, including land-use diversity and road intersection density.

REFERENCES

Batista Ferrer, H., Cooper, A., & Audrey, S. (2018). Associations of mode of travel to work with physical activity, and individual, interpersonal, organisational, and environmental characteristics. *Journal of Transport and Health*, *9*(October 2017), 45–55. https://doi.org/10.1016/j.jth.2018.01.009

Bekhor, S., & Shiftan, Y. (2010). Specification and estimation of mode choice model capturing similarity between mixed auto and transit alternatives. *Journal of Choice Modelling*, *3*(2), 29–49. https://doi.org/10.1016/S1755-5345(13)70034-4

Besser, L. M., & Dannenberg, A. L. (2005). Walking to public transit: Steps to help meet physical activity recommendations. *American Journal of Preventive Medicine*, *29*(4), 273–280. https://doi.org/10.1016/j.amepre.2005.06.010

Bopp, M., Gayah, V. V., & Campbell, M. E. (2015). Examining the link between public transit use and active commuting. *International Journal of Environmental Research and Public Health*, *12*(4), 4256–4274. https://doi.org/10.3390/ijerph120404256

Brown, A. E., Blumenberg, E., Taylor, B. D., Ralph, K., & Voulgaris, C. T. (2016). A taste for transit? Analyzing public transit use trends among youth. *Journal of Public Transportation*, *19*(1), 49–67. https://doi.org/10.5038/2375-0901.19.1.4

Buehler, R., & Hamre, A. (2015). The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. *Transportation*, *42*(6), 1081–1101.

https://doi.org/10.1007/s11116-014-9556-z

Clark, H. M. (2017). Who rides public transportation. In *American Public Transportation Association*. https://www.apta.com/resources/reportsandpublications/Documents/APTA-Who-Rides-Public-Transportation-2017.pdf

Edwards, R. D. (2008). Public transit, obesity, and medical costs: Assessing the magnitudes. *Preventive Medicine*, *46*(1), 14–21. https://doi.org/10.1016/j.ypmed.2007.10.004

Ermagun, A., Hossein Rashidi, T., & Samimi, A. (2015). A joint model for mode choice and escort decisions of school trips. *Transportmetrica A: Transport Science*, *11*(3), 270–289. https://doi.org/10.1080/23249935.2014.968654

Ermagun, A., & Levinson, D. (2017a). Public transit, active travel, and the journey to school: a cross-nested logit analysis. *Transportmetrica A: Transport Science*, *13*(1), 24–37. https://doi.org/10.1080/23249935.2016.1207723

Ermagun, A., & Levinson, D. (2017b). Public transit, active travel, and the journey to school: a cross-nested logit analysis. *Transportmetrica A: Transport Science*, *13*(1), 24–37. https://doi.org/10.1080/23249935.2016.1207723

Ermagun, A., Rashidi, T. H., & Lari, Z. A. (2015). Mode Choice for School Trips Long-Term Planning and Impact of Modal Specification on Policy Assessments. *Transportation Research Record*, *2513*, 97–105. https://doi.org/10.3141/2513-12

Ermagun, A., & Samimi, A. (2015). Promoting active transportation modes in school trips. *Transport Policy*, *37*, 203–211. https://doi.org/10.1016/j.tranpol.2014.10.013

Ermagun, A., & Samimi, A. (2016). How Are Children Accompanied to School? *Journal of Urban Planning and Development*, *142*(3), 04016002. https://doi.org/10.1061/(ASCE)up.1943-5444.0000315

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2008). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, *35*(1), 37–54. https://doi.org/10.1007/s11116-007-9136-6

Hasnine, M. S., Lin, T. Y., Weiss, A., & Habib, K. N. (2018). Determinants of travel mode choices of post-secondary students in a large metropolitan area: The case of the city of Toronto. *Journal of Transport Geography*, *70*(April 2017), 161–171. https://doi.org/10.1016/j.jtrangeo.2018.06.003

Hosmer, D. W., & Lemeshow, S. (1991). Applied Logistic Regression. In *Biometrics* (Vol. 47, Issue 4). https://doi.org/10.2307/2532419

Jiao, L., Berrington De Gonzalez, A., Hartge, P., Pfeiffer, R. M., Park, Y., Freedman, D. M., Gail, M. H., Alavanja, M. C. R., Albanes, D., Beane Freeman, L. E., Chow, W. H., Huang, W. Y., Hayes, R. B., Hoppin, J. A., Ji, B. T., Leitzmann, M. F., Linet, M. S., Meinhold, C. L., Schairer, C., … Stolzenberg-Solomon, R. Z. (2010). Body mass index, effect modifiers, and risk of pancreatic cancer: A pooled study of seven prospective cohorts. *Cancer Causes and Control*, *21*(8), 1305–1314. https://doi.org/10.1007/s10552-010-9558-x

Kontou, E., McDonald, N. C., Brookshire, K., Pullen-Seufert, N. C., & LaJeunesse, S. (2020). U.S. active school travel in 2017: Prevalence and correlates. *Preventive Medicine Reports*, *17*(November 2019), 101024. https://doi.org/10.1016/j.pmedr.2019.101024

Koppelman, F. S., & Bhat, C. (2006). A Self Instructing Course in Mode Choice Modeling : Multinomial and Nested Logit Models. In *Elements* (Vol. 28, Issue 3).

L. Gray, C., C. Messer, L., M. Rappazzo, K., S. Jagai, J., C. Grabich, S., & T. Lobdell, D. (2018). The association between physical inactivity and obesity is modified by five domains of environmental quality in U.S. adults: A cross-sectional study. *PLoS ONE*, *13*(8), 1–14. https://doi.org/10.1371/journal. pone.0203301

Lachapelle, U., & Frank, L. D. (2009). Transit and health: Mode of transport, employer-sponsored public transit pass programs, and physical activity. *Journal of Public Health Policy*, *30*(SUPPL. 1), 73–94. https://doi.org/10.1057/jphp.2008.52

Lachapelle, U., Frank, L., Saelens, B. E., Sallis, J. F., & Conway, T. L. (2011). Commuting by public transit and physical activity: where you live, where you work, and how you get there. *Journal of Physical Activity & Health*, *8 Suppl 1*(Suppl 1), 72–82. https://doi.org/10.1123/jpah.8.s1.s72

MacDonald, J. M., Stokes, R. J., Cohen, D. A., Kofner, A., & Ridgeway, G. K. (2010). The effect of light rail transit on body mass index and physical activity. *American Journal of Preventive Medicine*, *39*(2), 105–112. https://doi.org/10.1016/j.amepre.2010.03.016

Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. *Transportation Research Part A: Policy and Practice*, *124*(November), 82–114. https://doi.org/10.1016/j.tra.2018.12.015

McDonald, N. C. (2015). Are millennials really the “go-Nowhere” Generation? *Journal of the American Planning Association*, *81*(2), 90–103. https://doi.org/10.1080/01944363.2015.1057196

Mohiuddin, H. (2021). Planning for the first and last mile: A review of practices at selected transit agencies in the united states. *Sustainability (Switzerland)*, *13*(4), 1–19. https://doi.org/10.3390/su13042222

Nguyen, N. T., Nguyen, X. M. T., Lane, J., & Wang, P. (2011). Relationship between obesity and diabetes in a US adult population: Findings from the national health and nutrition examination survey, 1999-2006. *Obesity Surgery*, *21*(3), 351–355. https://doi.org/10.1007/s11695-010-0335-4

Ogden, C. L., Carroll, M. D., Kit, B. K., & Flegal, K. M. (2014). Prevalence of childhood and adult obesity in the United States, 2011-2012. *JAMA - Journal of the American Medical Association*, *311*(8), 806–814. https://doi.org/10.1001/jama.2014.732

Owen, C. G., Nightingale, C. M., Rudnicka, A. R., van Sluijs, E. M. F., Ekelund, U., Cook, D. G., & Whincup, P. H. (2012). Travel to school and physical activity levels in 9-10 year-old UK children of different ethnic origin; child heart and health study in England (CHASE). *PLoS ONE*, *7*(2), 1–8. https://doi.org/10.1371/journal.pone.0030932

Pabayo, R., Maximova, K., Spence, J. C., Ploeg, K. Vander, Wu, B., & Veugelers, P. J. (2012). The importance of Active Transportation to and from school for daily physical activity among children. *Preventive Medicine*, *55*(3), 196–200. https://doi.org/10.1016/j.ypmed.2012.06.008

Renne, J. L., Hamidi, S., & Ewing, R. (2016). Transit commuting, the network accessibility effect, and the built environment in station areas across the United States. *Research in Transportation Economics*, *60*(2016), 35–43. https://doi.org/10.1016/j.retrec.2017.02.003

Timperio, A., Veitch, J., & Sahlqvist, S. (2018). Built and physical environment correlates of active transportation. In *Children's Active Transportation*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-811931-0.00010-7

Train, K. E. (2009). Discrete choice methods with simulation, second edition. In *Discrete Choice Methods with Simulation, Second Edition* (Vol. 9780521766). https://doi.org/10.1017/CBO9780511805271

Turrell, G., Haynes, M., Wilson, L. A., & Giles-Corti, B. (2013). Can the built environment reduce health inequalities? A study of neighbourhood socioeconomic disadvantage and walking for transport. *Health and Place*, *19*(1), 89–98. https://doi.org/10.1016/j.healthplace.2012.10.008

U.S. Department of Transportation. (2018). *2017 NHTS Data User Guide* (Vol. 2018, Issue 301). https://nhts.ornl.gov/assets/2017UsersGuide.pdf

Voss, C., Winters, M., Frazer, A., & McKay, H. (2015). School-travel by public transit: Rethinking active transportation. *Preventive Medicine Reports*, *2*(October 2012), 65–70. https://doi.org/10.1016/j.pmedr.2015.01.004

Vovsha, P. (1997). Application of cross-nested logit model to mode choice in Tel Aviv, Israel, metropolitan area. *Transportation Research Record*, *1607*, 6–15. https://doi.org/10.3141/1607-02

Yatsuya, H., Yamagishi, K., North, K. E., Brancati, F. L., Stevens, J., & Folsom, A. R. (2010). Associations of obesity measures with subtypes of ischemic stroke in the ARIC study. *Journal of Epidemiology*, *20*(5), 347–354. https://doi.org/10.2188/jea.JE20090186

III. THE IMPACT OF COVID-19 ON TRANSIT AND TNC USE IN CALIFORNIA – What may happen after the pandemic?

INTRODUCTION

COVID-19 has deeply impacted people's mobility patterns, both globally (Arellana et al., 2020; Jenelius & Cebecauer, 2020; Orro et al., 2020; Park, 2020) and in the U.S. (Brough et al., 2021; Ehsani et al., 2021; Hu et al., 2021; Hu & Chen, 2021; Kim & Kwan, 2021; Liu et al., 2020). Public transportation and TNCs have not been spared by the pandemic (Du & Rakha, 2020; Hu & Chen, 2021; Kim & Kwan, 2021). As the Covid-19 pandemic is starting to wane, transportation planners and transit operators may wonder if the pre-Covid-19 trends observed in California will continue, with transit continuing to lose ridership while TNCs recover and soar to new heights, adding to urban congestion and making it more difficult for the state to reach its greenhouse gas reduction targets.

Transit has been especially hard hit by the pandemic. A national survey of 2,011 adults conducted online between June 17 and 29, 2020, shows that transit trips decreased by over 23% (Ehsani et al., 2021). Some areas were more affected than others. For instance, between mid-February to mid-May 2020, high-tech cities in the Bay Area and university cities such as Ithaca, NY, Ann Arbor, MI, and Madison, WI, experienced a steeper decline than cities in the South and the Midwest (Liu et al., 2020). In California, the impact of Covid-19 on transit has been brutal: San Francisco alone lost 94% of its transit ridership during the lockdown compared to before the pandemic (Toussaint, 2020).

Transportation network companies (TNCs, i.e., Uber and Lyft), which have been suspected of luring riders away from transit (Malalgoda & Lim, 2019; Manville et al., 2018; Sadowsky & Nelson, 2017), have also been affected. For example, by mid-March 2020, in Seattle alone, TNCs had lost over 60% of their riders due to the lockdown (Morshed et al., 2021). Moreover, California saw a complete shutdown of TNC services during the early months of the lockdown (Sainato, 2020).

Several studies have quantified the impact of Covid-19 on public transit and TNCs (Brough et al., 2021; Du & Rakha, 2020; Ehsani et al., 2021; Hu & Chen, 2021; Islam, 2020; Kim & Kwan, 2021; Liu et al., 2020). Authors of most of these early papers agree that the Covid-19 pandemic will trigger a paradigm shift in people's behavior due to health concerns, telecommuting spree, and financial capabilities (Morshed et al., 2021). However, except for Ehsani et al. (2021), who conducted a national survey representative of US adults, and Conway et al. (2020), who relied on a convenience survey of U.S. households, none of these studies have explored perceived future use of transit and TNCs. Ehsani et al. (2021) provided descriptive statistics of American adults' potential interests in transit, driving, walking, and biking, but they did not include TNCs in their analysis, and they did not provide a socio-economic profile of these users. Conway et al. (2020) were concerned with likely long-term behavioral changes in telecommuting, physical traveling, shopping, air traveling, meal deliveries, and air travel in the U.S., but their sample is limited to highly educated American adults, and they did not use a rigorous econometric modeling framework to derive their findings.

In this context, the purpose of this chapter is to explore how the Covid-19 pandemic has affected people's perceived use of transit and TNCs in California based on a random survey of Californians conducted by IPSOS for this project at the end of May 2021, which we analyzed using generalized ordered logit models. To the best of our knowledge, our investigation is the first to inquire about Californians’ willingness to take transit and TNCs after the pandemic is finally over.

In the next section, we review selected papers dealing with how the Covid-19 pandemic affected transit and TNC use. We then introduce our data, motivate our choice of variables, and introduce our modeling framework. After discussing our results, we summarize our findings, explore some policy implications, mention some limitations, and present some ideas for future work.

LITERATURE REVIEW

This section summarizes studies investigating the impact of the Covid-19 pandemic on public transit and TNCs. To find the papers we reviewed, we relied on Google Scholar. Our brief review has two parts: in the first part, we focus on the impacts of Covid-19 on transit ridership, and in the second part, we concentrate on TNC use. We conclude by summarizing some research gaps in this emerging literature to further motivate our study.

Covid-19 and transit ridership

Soon after the start of the Covid-19 pandemic, researchers started to investigate its impact on transit (Brough et al., 2021; Ehsani et al., 2021; Hu & Chen, 2021; Islam, 2020; Kim & Kwan, 2021; Liu et al., 2020).

Liu et al. (2020) analyzed mobility patterns in the U.S. based on massive amounts of real-time hourly and monthly transit data from transitapp.com, which they combined with socio-economic data from the 2018 American Community Survey (5 years estimates), and the number of COVID-19 cases and deaths from USA FACTS. Their study, which took place between mid-February and mid-May 2020, covers 113 counties (63 metro areas in 28 states). Findings from their logistic curve fitting, regressions, and ordinary Procrustes distance analyses show that communities with higher proportions of essential workers, vulnerable populations (such as African Americans, Females, Hispanics, and people over 45 years), and more coronavirus Google searches maintained higher levels of minimal transit demand during Covid-19. High-tech cities in the Bay area and university cities lost more transit riders than transit systems in the Midwest. Moreover, cities with more jobs that do not require a physical presence, young adults, and Caucasians saw larger drops in transit use.

Some studies also investigated transit ridership decline in the U.S. at different spatial scales: county (Kim & Kwan, 2021), census tract (Wilbur et al., 2020), block group (Hu & Chen, 2021), and transit stations (Hu & Chen, 2021).

Kim & Kwan (2021) observed a decline in transit at the county level and argued that it is highly correlated with the strictness of mobility restriction policies, poverty level, and political partisanship. The authors investigated individual travel between home and different locations (based on their mobile GPS) in 2,639 counties. They showed that, compared to the first wave (March-May 2020), people traveled more during the second wave (June-September 2020), even after heavy restrictions on mobility persisted, including in the most liberal counties in the U.S.

Wilbur et al. (2020) illustrated spatial and temporal variations of transit decline at the census tract level and associated it with socio-economic characteristics. They gathered average weekly ridership data from the Metropolitan Government of Nashville County and Chattanooga Area Regional Transportation Agency (CARTA). They reported that, compared to January-February, 2020, morning and evening peaks in May-June, 2020 lost more riders due to stay-at-home orders and remote work options. Moreover, this decline persisted even after lockdown restrictions were lifted, which shows that alternative work arrangements impacted transit use (Wilbur et al., 2020). Moreover, high-income tracts lost more riders (up to 19% more) than low-income tracts.

King County in Washington also experienced a transit use decline (Brough et al., 2021). Based on data collected at the census block groups from SafeGraph (with permission, it tracks precise locations of individual mobile devices), Brough et al. (2021) showed that between February and April 2020, when the overall mobility in King County declined by 57%, public transit use declined by an even sharper 74%. Like Nashville and Tennessee, transit decline in King County was more pronounced in areas with a larger percentage of highly educated and affluent residents (Brough et al., 2021).

At the station level, Hu & Chen (2021) investigated drops in transit ridership due to Covid-19 in Chicago based on historical ridership data (January 1, 2001, to April 30, 2020) provided by the Chicago Transit Authority (CTA). They found that Covid-19 impacted at least 95% of the stations in Chicago, pulling down transit ridership by 72.4% (Hu & Chen, 2021). Moreover, areas with more Caucasians, more educated, higher-income individuals, and a larger percentage of commercial land use lost more riders. Conversely, areas with more trade, transportation, and utility sectors experienced a smaller decline (Hu & Chen, 2021).

Many countries and major cities around the world experienced similar drops in transit patronage. For example, compared to the pre-Covid period, transit ridership during the early periods of the lockdown dropped 90% in Italy and France, 85% in Spain, 70% in the United Kingdom, and 70% in Germany (Falchetta & Noussan, 2020). Sweden (Jenelius & Cebecauer, 2020), Colombia (Arellana et al., 2020), India (Saha et al., 2020), and large cities such as Seoul (Park, 2020), Korea, also observed steep declines.

Table III-1. Summary of Selected Studies

Study (Year)	Data source and methodology	Variables	Key findings
Liu et al. (2020)	Transit app hourly and monthly transit demand data for 113 county-level transit systems in 63 metro areas and 28 states across the U.S.; USAFacts for daily county confirmed cases; American Community Survey (ACS) 5-year estimates (2014–2018). Logistic fitting, regression, and Procrustes distance analysis February 15-May 17 for monthly data; March 16-May 10, 2020, for hourly data	Key outcome parameters: minimum value of demand; initial and final dates when the decline in transit demand began and recessed; rate of decline; time lags. Explanatory variables: % of the population with non-physical occupations, African American population, people over 45 years, people commuting to work, households with no vehicles, and Google search trend index.	Transit demand declined more in cities in the Deep South and Midwest than in high-tech areas such as the Bay area (CA) and university cities such as Ithaca, Ann Arbor, and Madison. Greater transit decrease observed in populations that do not require a physical presence at work. Older people, African Americans mostly continued to use transit during the pandemic; the reverse happened for younger adults and Whites. Cities with more essential workers and larger vulnerable populations relied more on public transit during the pandemic
Kim & Kwan (2021)	Mobility data from 2639 counties (from home to different activities); American Community Survey (ACS) 5-years estimates; 2020 Presidential election results (McGovern 2020); USA Facts, 2020; Oxford COVID-19 Government Response Tracker Survey period: 1st March-30th September 2020 (7 months) Longitudinal data analysis methods: Growth model	*Dependent variable:* Monthly average distance (km) covered by an individual in a county. *Explanatory variables:* Percentage of people below the poverty level, population density, political partisanship, Covid-19 cases per capita, and county mobility restrictions.	Wave 1 (March-June 2020): mobility changes followed a V-shape trend, i.e., between March to April 2020, people's mobility declined and then recovered between April to June; mobility changes correlated with political partisanship, poverty, and the strictness of restrictions Wave 2 (June-September): mobility changes follow a weak linear pattern, i.e., little mobility declined despite strict restrictions and more severe COVID cases, even in more liberal democratic counties

Wilbur et al. (2020)	Study area: Nashville and Chattanooga, TN Data source: Metropolitan Government of Nashville and Davidson County; Chattanooga Area Regional Transportation Agency; US Census Bureau and Proximity One Study period: January 1, 2019, to July 1, 2020. Descriptive analysis	*Dependent variable:* average weekly ridership *Independent variable:* median Income, median housing value, median rent, race	In Nashville and Chattanooga, ridership declined by 66.9% and 65.1%, respectively, by late April 2020. Temporal investigation showed that ridership dropped significantly during the morning and evening peaks on weekdays, probably due to stay-at-home orders and remote work options Affluent census tracts in Nashville lost more riders than less-affluent tracts
Brough et al. (2021)	King County, Washington, U.S. Anonymized geolocated cell phone data from SafeGraph Inc., between February and April 2020; King County Metro automated passenger counter Descriptive statistics and OLS	Number of average daily activities in a census block group (CBG) between February and April 2020 Bus boarding data; ORCA and ORCA LIFT fare data *Explanatory Variable:* education, income	Average travel declined by 57% in all CBGs. CBGs where 10% of people have a bachelor's degree, saw a 45% travel drop; CBG where 90% of people have at least a bachelor's degree saw a 69% decline Drop in transit ridership steeper in more affluent areas than in poorer areas.
Hu & Chen (2021)	Twenty years (Jan 2001-April 2020) of daily transit ridership data from Chicago Transit Authority (CTA); Chicago Metropolitan Agency for Planning, 2017 ACS 5-year estimates; Chicago Data Portal; LEHD; National Climatic Data Center. Bayesian Structural Time Series (BSTS) model; infer impact of Covid 19; and Partial Least Squares (PTS) model	BSTS: *Dependent variable:* daily average ridership by station; *Explanatory variables:* holiday, daily max temperature and precipitation PTS: *Dependent variable:* % decrease in ridership caused by Covid-19; *Explanatory variables:* age, race, median income, education, job density, population density, % of jobs in different sectors (block group). Land use within 1 km buffer Covid-19: number of cases and deaths (by Zip Code)	COVID-19 impacted almost 95% of stations in Chicago, pulling down transit ridership by 72.4%. Areas with more White, educated, and high-income individuals and with more commercial land, lost more transit riders. Conversely, Areas with more trade, transportation, and utility sectors jobs, comparatively saw smaller declines. Regions with more severe cases/deaths saw smaller transit decline

Orro et al. (2020)	La Coruña, mid-sized city in Northwest Spain Study period: first half of 2020; baseline: 2017-2019 Descriptive statistics on average bus ridership	Variables: vehicle location, number of passengers boarding at each stop, and smart card operations. Analyzed changes in demand at stops, origin-destination flows and operation speeds, travel times, and reliability.	Pandemic hit bus transit harder than other modes. During lockdowns, bus use was 8–16% of baseline period (2017–2019); general traffic was 23–38%. After state declaration, ridership went down and remained at ~10-12% for the rest of the lockdowns. Reopening period saw a slow and gradual increase in ridership. Supply similar before the lockdown period and "new normal" period.
Jenelius & Cebecauer (2020)	Sweden (Stockholm, Västra Götaland and Skåne) Data from February 1 to May 31, 2019 (baseline), and 2020. Ridership data from the regional public transport authorities Descriptive analysis	Number of boardings by ticket type (Long: >=30 days, Short: 1–7 days, Single: single and travel funds, Special: special school and youth tickets), youths and seniors, and transport modes	Public transit lost more riders (40%-60%) than other modes. In the beginning, Stockholm and Skåne lost ~60% of its ridership; smaller drop in Västra Götaland Compared to 2019, the use of monthly cards remained the same; the number of Youth and school tickets dropped by 60% but recovered to around 50% of baseline by the end of May.
Arellana et al. (2020)	Investigation of the short-term impacts of Covid-19 policies on air, freight, and urban transport in Colombia. Seven largest cities in Colombia; 3 data sources for 16 weeks from February 21 to June 12, 2020. Covid Impact Dashboard; Covid-19 community mobility report; Transport operators	Variables: congestion changes; changes in the number of passengers compared to a baseline in all cities; changes in activity and travel behavior Variables: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential.	The mandatory quarantine between March 3 and April 13, 2020, dropped demand for public transport by 90%; trip reductions in public transport ~ less than for private modes because low-income people in dense areas widely use transit, and they did not stop traveling. Mandatory quarantine policies cut shopping, recreational activities, and park visits by 80%; commuting trips, pharmacy visits, and grocery travel decreased by 60%.

	Descriptive statistics and interviews of transport officials		
Park (2020)	Seoul Data Open Plaza; KCDC Data from 598 stations on 16 lines, for 2019 and from January 1 to March 31, 2020 Descriptive statistics: graphs; unpaired t-tests	Stations are divided into four categories: old, new, work, and leisure stations depending on their proximity to different land uses (university, business center, leisure center, etc.) and the % of senior passes. Variables: number of daily confirmed cases; number of daily passengers; free senior passes to the elderly.	Compared to the 3rd week of January, the 1st week of March saw a 40% decline in the mean daily number of passengers. No significant difference between old and new stations; leisure stations lost more passengers than work stations The first announcement of COVID-19 related deaths saw a massive drop in the total number of passengers. After a quick initial drop, the number of passengers picked up again due to decreases in level of perceived risk and adherence to social distancing

Covid-19 and TNC ridership

Covid-19 lockdowns caused Uber and Lyft a massive loss of riders and consequently revenues. In 2020, Uber trips shrank by 27% compared to 2019; however, UberEats revenues jumped 200% due to stay-at-home orders and online food delivery (Iqbal, 2021).

Du & Rakha (2020) conducted a comparative analysis between 2019 and 2020 (for a six-month interval, from January to June) and found that in Chicago, UberPool trips dropped by almost 71% during early March 2020 and entirely vanished by mid-March. They also reported that Uber's popularity for shorter trips (inter census tract trips) decreased by 40% (Du & Rakha, 2020).

A study in the greater Toronto area provided valuable information about TNC passenger characteristics during the pandemic (Loa et al., 2021). Loa et al. (2021) estimated an ordered Tobit model on a dataset collected through a web-based survey to understand the impact of Covid-19 on ride-sourcing services. They found that the share of frequent rideshare users changed as follows during the pandemic: 54% decreased their use, 17.7% increased it, and 28.4% continued as usual (Loa et al., 2021). They also found that students and transit pass owners frequently used this service during the pandemic to avoid transit due to health concerns. Finally, they concluded their analysis by stretching the importance of user attitudes towards ride-sourcing during an unprecedented time, especially their perception of risk.

Collaborative ventures between TNCs and transit agencies designed to serve first and last miles and exceptional services to senior citizens also collapsed because of lockdowns (Pho, 2020). At the beginning of the lockdown (Spring 2020), Conway et al. (2020) found that among the 1,308 highly educated U.S. adults, 20% expected to reduce their use of transit and TNCs compared to before the pandemic.

Table III-1 summarizes the studies we reviewed. In summary, our review suggests that stay-at-home orders impacted both transit and TNCs a great deal. Although we found two studies that investigated perceptions and intentions about the future use of transit and TNCs (Conway et al., 2020; Ehsani et al., 2021), an investigation for California based on a random sample and a rigorous modeling framework is still missing from the literature. Our goal in this chapter is to start filling that gap.

DATA

Our data come from a random survey of 1,026 Californians conducted by IPSOS in May 2021 for this project (which we called in this report the 2021 Covid-19 survey). This survey was administered to California members of KnowledgePanel, which is representative of the California population. Figure III.1 shows the location of the residential zip codes of respondents. We can see these locations overlap reasonably well with population density in California, with more respondents in large urban centers in northern, central, and southern California and some respondents in rural and less populated areas.

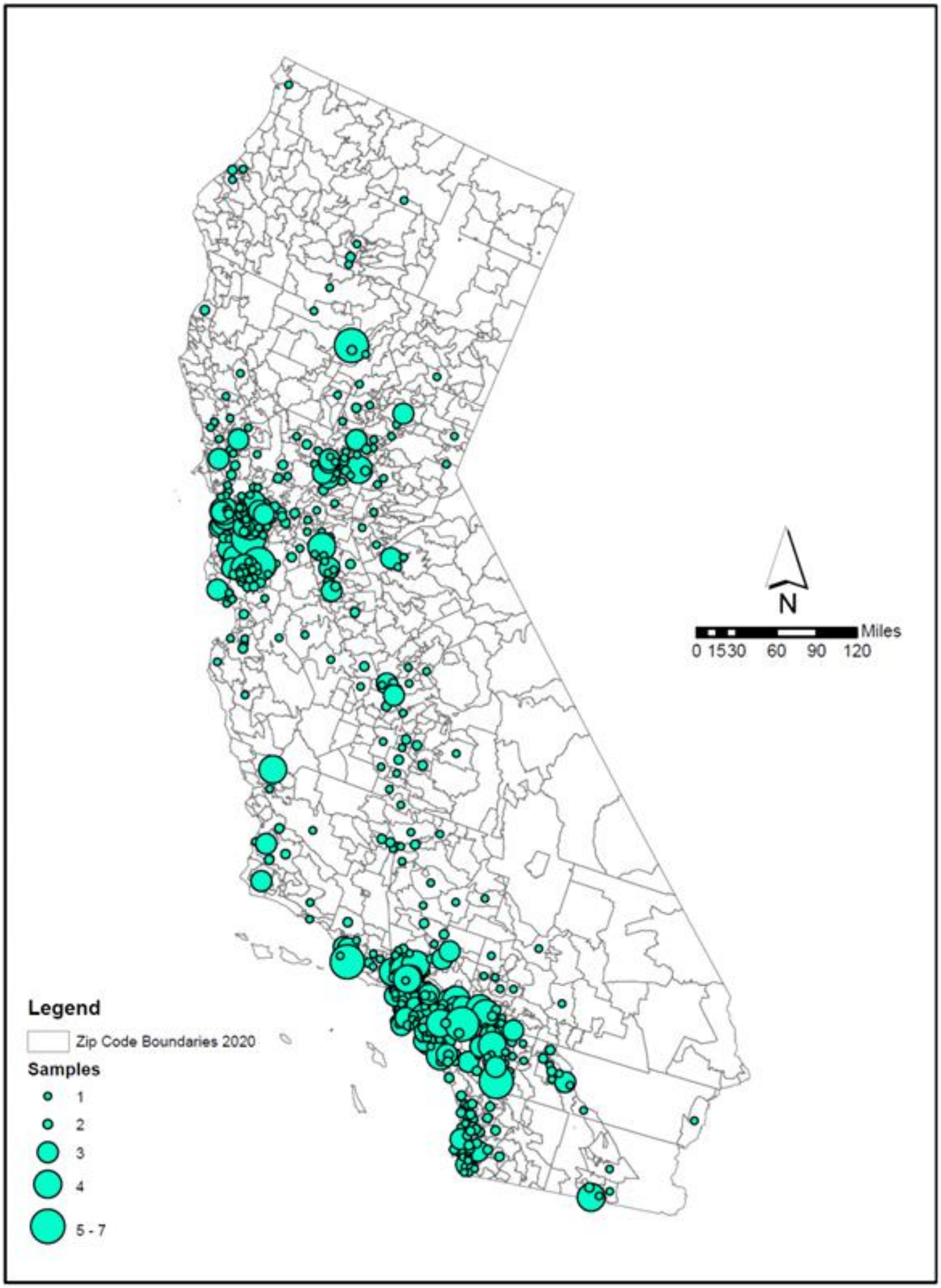


Figure III.1: Zip code location of respondents to the 2021 Covid-19 survey

Dependent Variables

We developed Generalized Ordered Logit models to explain expected changes in the use of each of four modes: driving, taking transit, walking/biking, and taking TNCs. For each mode, our dependent variables can take three values: 1 for "less than before Covid-19", 2 for "same as before Covid-19", and 3 for "more than before Covid-19". In addition, for each model, we included a rich set of explanatory variables known to impact transit use (see below).

Explanatory Variables

We selected our explanatory variables based on our literature review and the variables available in the 2021 COVID-19 survey. We divided our explanatory variables into three categories: individual-specific attributes, household-specific attributes, and land-use variables.

Individual specific attributes

We gathered the following information for each respondent in our sample from the person file: age, gender, race, Hispanic status, educational attainment, and occupation.

Many studies have considered age and gender for explaining transit and TNCs use preferences (Alemi et al., 2017; Alemi, Circella, & Sperling, 2018; Brown et al., 2016; Buehler & Hamre, 2015; Circella et al., 2017) (de Oña et al., 2016; Wan et al., 2016; Zhen et al., 2018). Therefore, we included age as generation variables (Four binary variables: Generation Z & Y, Generation X, Baby boomers and Silent and G.I. Generation; baby boomers serve as a baseline) and gender as a binary variable in our model.

The literature also suggests that individual educational attainment and occupation play a pivotal role in transit and TNC ridership (Alemi et al., 2017; Alemi, Circella, & Sperling, 2018; Brown et al., 2016; Buehler & Hamre, 2015; Circella et al., 2017; Clark, 2017; Grahn et al., 2020). To capture the level of education, we created four binary variables: high school or less, some college or associate degree, undergraduate degree (our baseline), and graduate or professional degree.

Similarly, for occupation, we created five categories: 1) sales and service; 2) clerical or administrative support; 3) manufacturing, construction, maintenance, or farming; 4) professional, managerial, or technical; and 5) others (only for COVID-19 survey).

Race and Hispanic status play an important role in transit and TNC use (Alemi et al., 2017; Brown et al., 2016; Buehler & Hamre, 2015; Circella et al., 2017; Grahn et al., 2020; Harold M.kohm, n.d.). Based on the distribution of the race of our respondents, we created four binary variables: Caucasian, African American, Asian, and Other. The "Other" category captures the remaining choices for race. Hispanic status was determined similarly.

Household specific attributes

Our models also include standard household variables such as annual household income, household size, vehicle ownership, and homeownership, which have been found to matter for explaining household travel preferences (Clark, 2017).

Table III-2. Summary Statistics (N=1,022)

	Mean	Min	Max
Individual specific variables			
Generation			
Generations Z & Y	0.251	0	1
Generation X	0.285	0	1
Baby boomers	0.375	0	1
Silent and GI Generations	0.089	0	1
Gender (Male = 1)	0.513	0	1
Hispanic status (1 if Hispanic, 0 otherwise)	0.275	0	1
Ethnicity			
Caucasian	0.743	0	1
African American	0.061	0	1
Asian	0.137	0	1
Other	0.060	0	1
Educational attainment			
Less than high school & high school	0.267	0	1
Some college or associate degree	0.310	0	1
Undergraduate degree	0.243	0	1
Graduate or professional degree	0.180	0	1
Occupation			
Sales and service	0.150	0	1
Clerical or administrative support	0.096	0	1
Manufacturing, construction, maintenance, or farming	0.067	0	1
Professional, managerial, or technical	0.160	0	1
Other	0.094	0	1
Household specific variables			
Annual household income			
<$25,000	0.102	0	1
$25,000-$49,999	0.150	0	1
$50,000-$74,999	0.144	0	1
$75,000-$99,999	0.147	0	1
$100,000-$149,999	0.197	0	1
>=$150,000	0.261	0	1
Change in household income during Covid-19			
It decreased	0.181	0	1
It did not change	0.569	0	1
It increased	0.155	0	1
Does not know about HH income change	0.091	0	1
Household owns home (1 if true)	0.659	0	1
Number of people in the household	2.773	1	10
Changes in number of household vehicles during Covid-19			
It decreased	0.038	0	1

It did not change	0.921	0	1
It increased	0.041	0	1
Land use			
Population density (1000 persons/acres)	9.074	0.004	88.780

We collapsed the seven categories in the 2021 COVID-19 survey into six binary categories to represent annual household income, with \$50,000-\$74,999 as our baseline. In addition, we added four variables for the Covid-19 survey questions that captured the changes in household income during the pandemic (household income increased, decreased, remained changed, and unknown).

We also created a binary variable to code homeownership and a count variable for household members. Since the Covid-19 survey did not ask for the number of household drivers, we created three binary variables to capture changes in mobility restrictions associated with car ownership indirectly: the number of household vehicles increased, decreased, or remained unchanged (baseline) during the pandemic compared to before.

Land use

Our literature review (Alemi, Circella, Mokhtarian, et al., 2018; Buehler & Hamre, 2015; Clark, 2017; Frankena, 1976; Jaafar Sidek et al., 2020) showed the importance of capturing geographical variation in evaluating passenger's perception of transit and TNC use. For our COVID-19 survey, we simply relied on population density (people/acres) by zip code.

We lost a few observations to missing variables (non-response) in our Covid-19 survey, for which our final sample is 975. Table III-2 presents descriptive statistics for the explanatory variables in the generalized ordered logit models estimated for this chapter.

MODELS

To explain ordered limited dependent variables such as answers to a survey question collected on a Likert scale, the starting point model is often an ordered logit model (Long, 1997). Assuming there are M possible choices, the probability that respondent *i* chooses an alternative higher than $m \in \{1,\ldots,M-1\}$ is given by

$$\Pr(Y_i > m) = \frac{\exp(\boldsymbol{X}_i\boldsymbol{\beta}' - \tau_m)}{1+\exp(\boldsymbol{X}_i\boldsymbol{\beta}' - \tau_m)} \qquad (1)$$

where $\boldsymbol{X}_i$ is a vector of observed explanatory variables, $\boldsymbol{\beta}$ is a vector of unknown parameters, and the τ_ms (m=1,…,M-1) are unknown thresholds to estimate jointly with $\boldsymbol{\beta}$.

For respondent *i* and alternative $m \in \{1,\ldots,M-1\}$, the odds Ω_{im}, is defined by

$$\Omega_{im} = \frac{\Pr(Y_i > m)}{\Pr(Y_i \leq m)} = \exp(\boldsymbol{X}_i\boldsymbol{\beta}' - \tau_m), \qquad (2)$$

so the ratios of the odds for two different respondents and the same alternative can be shown to be independent of that alternative. This property, which is called the proportional odds assumption (or the parallel line assumption), is an implication of the ordered logit model. In practice, this assumption often does not hold (Long & Freese, 2014). An alternative is the generalized ordered logit model (e.g., see Peterson & Harrell, 1990), where the βs can depend on the alternative considered. However, explaining results in this context is somewhat convoluted because we need to compare people who expect to use a mode at least as much after the pandemic compared to before, with people who expect to use it strictly more.

For simplicity, we present instead two simple logit models for each mode: one that compares respondents who expect to use that mode strictly less after the pandemic compared to before (versus at least as much), and the other that contrasts respondents who expect to use that mode strictly more after the pandemic compared to before (versus at most as much).

As is usual for logit models, we present results in terms of odds ratios, which for explanatory variable k can be written (Long, 1997):

$$\Omega_{ik} = \left(\frac{\Pr(Y_i=1|X_{i(k+1)})}{\Pr(Y_i=0|X_{i(k+1)})}\right) / \left(\frac{\Pr(Y_i=1|X_i)}{\Pr(Y_i=0|X_i)}\right) = \exp(\beta_k) \tag{3}$$

In Equation (3), Xi(k+1) is the vector of explanatory variables for respondent i modified by adding 1 to the kth explanatory variable.

RESULTS

Our econometric work was performed using Stata 17. Before interpreting our logit results, it is helpful to graph our explanatory variables.

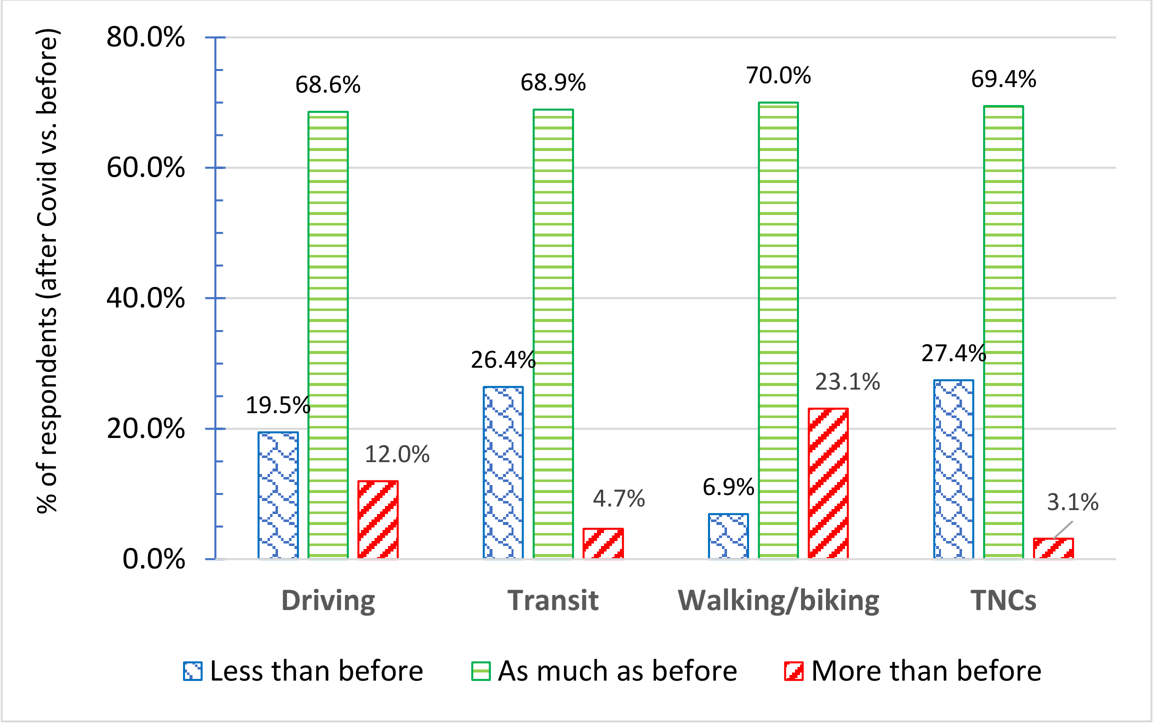


Figure III.2. Expected change in use of various modes (after vs. before the pandemic)

Figure III.2 shows that slightly over two-thirds of respondents plan to use transportation modes at their disposal as often after the pandemic as before. However, the remaining third of Californians expect to make some substantial mode changes. Three modes could come down on the losing side: driving (19.5% less vs. 12.0% more), and especially transit (26.4% less vs. 4.7%), and TNCs (27.4% less and 3.1% more). Having over 19.5% of Californians drive less is good news for the state's efforts to reduce VMT in the fight for reducing greenhouse gas emissions, although we do not know how much less these respondents will drive and how much more the 12% planning on driving more will drive. Moreover, our survey does not capture how much driving may change because of population growth and economic expansion, especially as online shopping keeps increasing and California's logistics industry continues to expand. Conversely, many more Californians (23.1%) plan on walking and biking more after the pandemic than before, than are planning on walking and biking less (6.9%), which is encouraging.

Let us now analyze the characteristics of various groups of Californians who are planning on altering their transportation mode mix after the pandemic compared to before. Results, in the form of odds ratios, are presented in Table III-3. Non-significant coefficients have been replaced with "- -" to help focus on statistically significant coefficients. Since odds ratios close to one indicate a lack of practical significance, we report them without comments.

Logit Models Results

Driving

First, we see that compared to respondents with an undergraduate degree, respondents with some college or an associate degree (OR=0.50**) are not thinking they will be driving less post-pandemic. The same applies to people who work in sales (OR=0.45**) or who have an "other" occupation (OR=0.49*) compared to people who have a professional, managerial, or technical job. Conversely, many Hispanics (OR=1.69*) think they will be driving less after Covid-19. Since some Hispanics (OR=2.34**) are also planning on driving more, the sub-group that shrank is Hispanics who will be driving as much after as they were before the pandemic. The other groups likely to drive more post-pandemic are Asians (OR=2.35*), people with at most a high school education (OR=2.21*), and people unsure about how the pandemic affected their household income (OR=2.72*).

Transit

From Figure III.2, we know that many Californians plan to use transit less after the pandemic. This seems the case across the board since only a handful of coefficients for that logit model are statistically significant, but it is especially true for Hispanic (OR=1.78**) and Asian (OR=2.97***) respondents, and for people whose households increased the number of their vehicles during the pandemic (OR=2.60*), presumably to avoid transit. Only men appear less likely to use transit less (OR=0.62*), and only households whose income increased during Covid-19 (OR=1.55*) seem willing to increase their use of transit post-pandemic.

Table III-3. Mode Change Models Results (N=1,022)

	Expected use of each mode after Covid-19 compared to before							
	Driving		**Transit**		**Walking/biking**		**TNCs**	
	Less	More	Less	More	Less	More	Less	More
Individual specific variables								
Generation (base=Baby Boomer)								
Generations Z & Y	- -	- -	- -	- -	- -	- -	- -	- -
Generation X	- -	- -	- -	- -	- -	- -	- -	- -
Silent and GI Generations	- -	- -	- -	- -	- -	- -	- -	- -
Gender (Male = 1)	- -	- -	0.62*	- -	- -	- -	- -	- -
Hispanic status (Hispanic =1)	1.69*	2.34**	1.78*	- -	2.33***	2.54***	- -	- -
Ethnicity (base=White)								
African American	- -	- -	- -	- -	2.78***	2.68**	- -	- -
Asian	- -	2.35*	2.97***	- -	2.19***	2.50***	- -	- -
Other	- -	- -	- -	- -	2.10*	2.42**	- -	- -
Educational attainment (base=undergraduate degree)								
Less than high school & high school	- -	2.21*	- -	- -	- -	2.08**	- -	0.22*
Some college or associate degree	0.50**	- -	- -	- -	- -	- -	0.28*	0.24*
Graduate or professional degree	- -	- -	- -	- -	- -	- -	- -	- -
Occupation								
Sales and service	0.45**	- -	- -	- -	- -	- -	- -	- -
Clerical or administrative support	- -	- -	- -	- -	- -	- -	- -	- -
Manufacturing, construction, maintenance, farming	- -	- -	- -	- -	- -	- -	- -	- -
Other	0.49*	- -	- -	- -	- -	- -	- -	- -
Household specific variables								
Annual household income								
<$25,000	- -	- -	- -	- -	- -	- -	- -	- -
$25,000-$49,999	- -	- -	- -	- -	1.94*	- -	- -	- -

$75,000-$99,999	- -	- -	- -	- -	- -	- -	- -	- -
$100,000-$149,999	- -	- -	- -	- -	- -	- -	- -	- -
>=$150,000	- -	- -	- -	- -	- -	- -	- -	- -
Changes in household income during Covid-19								
HH income decreased	- -	- -	- -	1.55*	- -	- -	- -	- -
HH income increased	- -	- -	- -	- -	- -	- -	- -	- -
Does not know about HH income change	- -	2.72*	- -	- -	- -	1.76*	- -	- -
Household owns home	- -	- -	- -	- -	- -	- -	- -	0.29**
Number of people in the household	- -	- -	- -	- -	0.89*	- -	- -	1.29*
Changes in # of household vehicles during Covid-19								
It decreased	- -	- -	- -	- -	- -	- -	- -	5.49**
It increased	- -	- -	2.60*	- -	2.13*	- -	- -	- -
Land use								
Population density (1000 persons/acres)	- -	- -	- -	- -	- -	- -	1.02*	- -

1. * p<0.05, ** p<0.01, *** p<0.001.
2. The table above displays the odds ratio (OR) of each explanatory variable.

Walking/biking

The situation appears brighter for walking and biking (Figure III.2), which are expected to increase, although surprisingly not for all Californians. The picture is mixed. On the one hand, some Hispanics (OR=2.33***) compared to non-Hispanics, but also some African Americans (OR=2.78***), some Asians (OR=2.19***), and some members from the "other" group (OR=2.10*) are expecting to walk and bike less after the pandemic compared to non-Hispanics and Whites, respectively. On the other hand, members from the same groups (OR=2.54*** for Hispanics, OR=2.68** for African Americans, OR=2.50*** for Asians, and OR=2.42** for others) are planning on walking and biking more after the pandemic, which suggests some inherent heterogeneity within these groups, and possibly some different circumstances (related for example to safety and the presence of walking/biking infrastructure) that are not reflected in our explanatory variables.

A few other variables are statistically significant. Households with an annual income between $25,000 and $50,000 indicate they would likely walk and bike less after Covid-19 (OR=1.94*), and so will households whose annual income increased during the pandemic (OR=2.13*). In contrast, the reverse holds for larger households (OR=0.89*). Conversely, respondents with at most a high school education intend to walk and bike more (OR=2.08**).

TNCs

After the pandemic, intentions towards using TNCs seem even less favorable than for transit (Figure III.2). The limited number of statistically significant coefficients suggests that these intentions are widespread among Californians. There are a few exceptions. Some less-educated respondents are less likely (OR=0.28* for some college or an associate degree) to use TNCs less after the pandemic. In contrast, others are less likely to use them more (OR=0.22* for those with at most a high school education, OR=0.24* for people with some college and an associate degree), which again reflects some group heterogeneity. The same applies to people who own their home (OR=0.29*), but the opposite holds for larger households (OR=1.29*) and especially for households who gained access to more motor vehicles during the pandemic (OR=5.49**).

CONCLUSIONS

In this chapter, we estimated some logit models to explore Californians' intentions about using different modes (driving, transit, walking and biking, and TNCs) for any travel purpose after the pandemic is over based on results from a random survey of Californians conducted by IPSOS in late May 2021 for this research project.

While for each mode, between 68% and 70% of respondents anticipated no change, three modes could experience substantial drops in popularity: driving, transit, and TNCs. A decrease in driving would reduce VMT and help the state achieve its greenhouse gas reduction target. However, nobody can say at this point if the intention by 19.5% of our respondents to reduce driving will be sufficient to substantially offset another 12% of our respondents who intend to drive more, partly as they decrease their use of transit.

Results for transit are grim: over 26% of our respondents intend to use transit less after Covid, and only 4.7% would like to use transit more post-Covid-19. While this drop appears to affect a broad range of Californians, it seems to disproportionately affect Hispanics, Asians, and women, many of which had been sustaining ridership until before the pandemic. Likewise, respondents from a broad range of backgrounds indicated their intention to use TNCs less after Covid-19.

A silver lining to these results is a substantial uptick in intentions to walk and bike more (+23.1%), although just under 7% of our respondents announced opposite intentions. Surprisingly, results were mixed among Hispanics, African Americans, and Asians, with relatively large percentages of respondents in each category stating their intent to walk and bike more, while almost equally large percentages stated the opposite.

One limitation of this work is that our models include only one land use variable (population density). A second limitation is that not all respondents may have access to transit, so support for transit's status quo was likely overstated.

Future research could re-estimate models with additional land-use variables (especially as they relate to transit and the walking/biking infrastructure) and try to understand the heterogeneity of intentions to use various transportation modes after the pandemic among Hispanics, African Americans, and Asians to gage, for example, the quality of their access to transit, biking, and walking infrastructure.

REFERENCES

Alemi, F., Circella, G., Handy, S., & Mokhtarian, P. (2017). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Transportation Research Board 96th Annual Meeting*. https://trid.trb.org/view/1529007

Alemi, F., Circella, G., Mokhtarian, P., & Handy, S. (2018). On-demand Ride Services in California: Investigating the Factors Affecting the Frequency of Use of Uber/Lyft. *Transportation Research Board 97th Annual Meeting*, *7550*.

Alemi, F., Circella, G., & Sperling, D. (2018). Adoption of Uber and Lyft, Factors Limiting and/or Encouraging Their Use and Impacts on Other Travel Modes among Millennials and Gen Xers in California. *Transportation Research Board 97th Annual Meeting*.

Arellana, J., Márquez, L., & Cantillo, V. (2020). COVID-19 Outbreak in Colombia: An Analysis of Its Impacts on Transport Systems. *Journal of Advanced Transportation*, *2020*, 1DUMMMY. https://doi.org/10.1155/2020/8867316

Brough, R., Freedman, M., & Phillips, D. C. (2021). Understanding socio-economic disparities in travel behavior during the COVID-19 pandemic. *Journal of Regional Science*, *June*. https://doi.org/10.1111/jors.12527

Brown, A. E., Blumenberg, E., Taylor, B. D., Ralph, K., & Voulgaris, C. T. (2016). A taste for transit? Analyzing public transit use trends among youth. *Journal of Public Transportation*, *19*(1), 49–67. https://doi.org/10.5038/2375-0901.19.1.4

Buehler, R., & Hamre, A. (2015). The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. *Transportation*, *42*(6), 1081–1101.

https://doi.org/10.1007/s11116-014-9556-z
Circella, G., Alemi, F., Berliner, R., Tiedeman, K., Lee, Y., Fulton, L., Handy, S. L., & Mokhtarian, P. L. (2017). The Multimodal Behavior of Millennials: Exploring Differences in Travel Choices between Young Adults and Gen Xers in California. *Transportation Research Board 96th Annual Meeting*, *110*(9), 1689–1699.
Clark, H. M. (2017). Who rides public transportation. In *American Public Transportation Association*. https://www.apta.com/resources/reportsandpublications/Documents/APTA-Who-Rides-Public-Transportation-2017.pdf
Conway, M. W., Salon, D., da Silva, D. C., & Mirtich, L. (2020). How Will the COVID-19 Pandemic Affect the Future of Urban Life? Early Evidence from Highly-Educated Respondents in the United States. *Urban Science*, *4*(4), 50. https://doi.org/10.3390/urbansci4040050
de Oña, J., de Oña, R., Diez-Mesa, F., Eboli, L., & Mazzulla, G. (2016). A composite index for evaluating transit service quality across different user profiles. *Journal of Public Transportation*, *19*(2), 128–153. https://doi.org/10.5038/2375-0901.19.2.8
Du, J., & Rakha, H. A. (2020). COVID-19 Impact on Ride-hailing: The Chicago Case Study. *Findings*, *2018*(November 2018), 1–7. https://doi.org/10.32866/001c.17838
Ehsani, J. P., Michael, J. P., Duren, M. L., Mui, Y., & Porter, K. M. P. (2021). Mobility Patterns Before, During, and Anticipated After the COVID-19 Pandemic: An Opportunity to Nurture Bicycling. *American Journal of Preventive Medicine*, *60*(6), e277–e279. https://doi.org/10.1016/j.amepre.2021.01.011
Falchetta, G., & Noussan, M. (2020). The Impact of COVID-19 on Transport Demand, Modal Choices, and Sectoral Energy Consumption in Europe. In *IAEE Energy Forum / COVID-19 Issue 2020*. https://www.iaee.org/en/publications/newsletterdl.aspx?id=884
Frankena, M. (1976). The Demand for Urban Bus Transit in Canada. *Journal of Transport Economics and Policy*, *12*(3), 280–303.
Grahn, R., Harper, C. D., Hendrickson, C., Qian, Z., & Matthews, H. S. (2020). Socioeconomic and usage characteristics of transportation network company (TNC) riders. *Transportation*, *47*(6), 3047–3067. https://doi.org/10.1007/s11116-019-09989-3
Harold M.kohm. (n.d.). Factors affecting Urban Transit Ridership. *Factors Affecting Urban Transit Ridership*.
Hu, S., & Chen, P. (2021). Who left riding transit? Examining socio-economic disparities in the impact of COVID-19 on ridership. *Transportation Research Part D: Transport and Environment*, *90*(December 2020), 102654. https://doi.org/10.1016/j.trd.2020.102654
Hu, S., Xiong, C., Liu, Z., & Zhang, L. (2021). Examining spatiotemporal changing patterns of bike-sharing usage during COVID-19 pandemic. *Journal of Transport Geography*, *91*(December 2020). https://doi.org/10.1016/j.jtrangeo.2021.102997
Iqbal, M. (2021). Uber Revenue and Usage Statistics (2017). *Business of Apps*. https://www.businessofapps.com/data/uber-statistics/
Islam, A. (2020). *The Impact of COVID-19 & Safer-at-Home Policies on U.S. Public Transit* (Issue September, pp. 1–38). http://hdl.handle.net/10393/41895
Jaafar Sidek, M. F., Bakri, F. A., Kadar Hamsa, A. A., Aziemah Nik Othman, N. N., Noor, N. M., & Ibrahim, M. (2020). Socio-economic and Travel Characteristics of transit users at Transit-oriented Development (TOD) Stations. *Transportation Research Procedia*, *48*(2019), 1931–

1955. https://doi.org/10.1016/j.trpro.2020.08.225

Jenelius, E., & Cebecauer, M. (2020). Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. *Transportation Research Interdisciplinary Perspectives*, *8*. https://doi.org/10.1016/j.trip.2020.100242

Kim, J., & Kwan, M. P. (2021). The impact of the COVID-19 pandemic on people's mobility: A longitudinal study of the U.S. from March to September of 2020. *Journal of Transport Geography*, *93*(December 2020), 103039. https://doi.org/10.1016/j.jtrangeo.2021.103039

Liu, L., Miller, H. J., & Scheff, J. (2020). The impacts of COVID-19 pandemic on public transit demand in the United States. *PLoS ONE*, *15*(November 11), 1–22. https://doi.org/10.1371/journal.pone.0242476

Loa, P., Hossain, S., Liu, Y., & Nurul Habib, K. (2021). How have ride-sourcing users adapted to the first wave of the COVID-19 pandemic? evidence from a survey-based study of the Greater Toronto Area. *Transportation Letters*, *13*(5–6), 404–413. https://doi.org/10.1080/19427867.2021.1892938

Malalgoda, N., & Lim, S. H. (2019). Do transportation network companies reduce public transit use in the U.S.? *Transportation Research Part A: Policy and Practice*, *130*(October), 351–372. https://doi.org/10.1016/j.tra.2019.09.051

Manville, M., Taylor, B. D., & Blumenberg, E. (2018). *Falling Transit Ridership: California and Southern California*. https://escholarship.org/uc/item/0455c754

Morshed, S. A., Khan, S. S., Tanvir, R. B., & Nur, S. (2021). Impact of COVID-19 pandemic on ride-hailing services based on large-scale Twitter data analysis. *Journal of Urban Management*, *10*(2), 155–165. https://doi.org/10.1016/j.jum.2021.03.002

Orro, A., Novales, M., Monteagudo, Á., Pérez-López, J. B., & Bugarín, M. R. (2020). Impact on city bus transit services of the COVID-19 lockdown and return to the new normal: The case of A Coruña (Spain). *Sustainability (Switzerland)*, *12*(17). https://doi.org/10.3390/su12177206

Palm, M., Allen, J., Liu, B., Zhang, Y., Widener, M., & Farber, S. (2021). Riders Who Avoided Public Transit During COVID-19. *Journal of the American Planning Association*, *0*(0), 1–15. https://doi.org/10.1080/01944363.2021.1886974

Park, J. (2020). Changes in Subway Ridership in Response to COVID-19 in Seoul, South Korea: Implications for Social Distancing. *Cureus*, *12*(4), 2–10. https://doi.org/10.7759/cureus.7668

Pho, B. (2020). *Orange County's Outsourcing of Public Transit to Lyft Nearly Left Residents Stranded*. https://voiceofoc.org/2020/08/orange-countys-outsourcing-of-public-transit-to-lyft-nearly-left-residents-stranded/

Sadowsky, N., & Nelson, E. (2017). The Impact of Ride-Hailing Services on Public Transportation Use: A Discontinuity Regression Analysis. *Economics Department Working Paper Series*, 28. http://digitalcommons.bowdoin.edu/econpapers%0Ahttp://digitalcommons.bowdoin.edu/econpapers/13%0Ahttp://digitalcommons.bowdoin.edu/econpapers%0Ahttp://digitalcommons.bowdoin.edu/econpapers/13%0Ahttps://digitalcommons.bowdoin.edu/econpapers/13

Saha, J., Barman, B., & Chouhan, P. (2020). Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports,

2020. *Children and Youth Services Review*, *116*(June), 105160. https://doi.org/10.1016/j.childyouth.2020.105160
Sainato, M. (2020). California Uber and Lyft drivers brace for shutdown over worker classification. *The Guardian*. https://www.theguardian.com/business/2020/aug/19/california-uber-and-lyft-drivers-brace-for-shutdown-over-worker-classification
Toussaint, B. Y. K. (2020, May). Post-pandemic public transit may not end up looking all that different — but its goals may have to change. *Fast Company*, 1. https://www.fastcompany.com/90510287/post-pandemic-public-transit-may-not-end-up-looking-all-that-different-but-its-goals-may-have-to-change
Wan, D., Kamga, C., Liu, J., Sugiura, A., & Beaton, E. B. (2016). Rider perception of a "light" Bus Rapid Transit system - The New York City Select Bus Service. *Transport Policy*, *49*, 41–55. https://doi.org/10.1016/j.tranpol.2016.04.001
Wilbur, M., Ayman, A., Ouyang, A., Poon, V., Kabir, R., Vadali, A., Pugliese, P., Freudberg, D., Laszka, A., & Dubey, A. (2020). Impact of COVID-19 on Public Transit Accessibility and Ridership. *ArXiv Preprint ArXiv:2008.02413.* http://arxiv.org/abs/2008.02413
Zhen, F., Cao, J., & Tang, J. (2018). Exploring correlates of passenger satisfaction and service improvement priorities of the Shanghai-Nanjing High Speed Rail. *Journal of Transport and Land Use*, *11*(1), 559–573. https://doi.org/10.5198/jtlu.2018.958

IV. THEIR WAY OR THE HIGHWAY? Californians' perception of transit before and during Covid-19

INTRODUCTION

California relies on public transportation to meet its ambitious greenhouse gas reduction targets and provide mobility services to disadvantaged communities (Caltrans, 2021). However, despite considerable bus and rail transit investments, transit ridership in the state has continued to fall, especially since 2014, with a few exceptions locally (Taylor et al., 2020). Even the Bay area, which had done relatively well before 2017, experienced a drop of over 27 million annual boardings between 2017 and 2018 (Taylor et al., 2020). The Covid-19 pandemic compounded an already precarious situation, with San Francisco alone losing 94% of its ridership during the pandemic compared to before (Toussaint, 2020). As the pandemic starts to wane, one of California's top mobility challenges is delivering an immediate equitable, safe, and economically inclusive public transportation system to disadvantaged communities and upholding its long-term vision of providing a carbon-neutral transportation system (Caltrans, 2021).

Why has transit been losing its ridership in California? Several explanations have been proposed in the transportation literature. They include external factors such as fuel price changes, increasing access to private vehicles (especially for lower-income households), rising incomes and evolving employment conditions, and the continued prevalence of dispersed settlements that require driving (Manville et al., 2018; Taylor et al., 2020). In addition, the growth of new mobility options like Uber and Lyft likely contributed to taking away some of transit's ridership (Manville et al., 2018). Finally, transit service quality also plays a vital role in determining its success (Malalgoda & Lim, 2019; Manville et al., 2018). Overall changes in transit supply variables, fares, subsidies, convenience, and safety likely also contributed to declines in transit ridership (Manville et al., 2018). For example, between 2005 and 2013, bus speeds in the LA metro fell by 13% (Manville et al., 2018).

In this context, examining feedback from transit users is essential for transit agencies to stem the decline in ridership and hopefully gain new users (Eboli & Mazzulla, 2011; Machado-León et al., 2016; Wan et al., 2016). Although several studies have investigated the impact of transit services on falling transit ridership in California (Manville et al., 2018; Taylor et al., 2020), they have not (to the best of our knowledge) analyzed Californians' perceptions of transit. The purpose of this chapter is, therefore, to examine Californians' perception of transit and what obstacles stand in the way of increasing transit use based on 2017 NHTS data. Since the Covid-19 pandemic may have added hurdles to transit use, our second contribution is to examine reasons why Californians may not use transit more after the pandemic based on a May-June 2021 random survey of Californians conducted by IPSOS for this project.

In the next section, we briefly review selected studies before presenting our data and our modeling approach. We then discuss our results, summarize our conclusions, mention some limitations of our work, and suggest future research directions.

LITERATURE REVIEW

U.S. and Canada

It is well known that transit service attributes play a pivotal role in customer satisfaction. These attributes range from reliability and schedules to the safety and comfort of the transit infrastructure.

An investigation of 1,700 Bus Rapid Transit (BRT) riders in New York City (NYC) revealed that service frequency, vehicle speed, and on-time performance have a significant positive impact on customer satisfaction (Wan et al., 2016). Other factors impacting customer satisfaction with BRT are the fare payment system, hours of operations, and how concerns are handled (Wu et al., 2020). In addition, Wu et al. (2018) showed that local bus users' preferences differ from those of BRT users. For the former, reliability, reasonable travel time, and personal safety at stops are critical (Wu et al., 2018).

Our investigation also revealed that some riders put more weight on on-board performance, while others prefer good physical infrastructure when they wait for a bus or a train (Fan et al., 2016; Lagune-Reutler et al., 2016; Park et al., 2021). A user satisfaction survey in Minneapolis, MN, showed that stops with shelters, benches, and trees make waiting more acceptable (Fan et al., 2016). Park et al. (2021) surveyed 445 riders in Utah to explore the relationship between first and last-mile experience with user satisfaction. They reported that riders are concerned about traffic and crime safety at transit stops. Moreover, improvements in out-of-vehicle environments such as safety and transfer experiences weigh more than in-vehicle improvements (Park et al., 2021).

Transit satisfaction can also be tied to its geographical location and to rider type. By spatially segmenting transit riders in the greater Hamilton area in Canada, Grisé & El-Geneidy (2018) showed that frequent transit riders who live in the proximity of a train station (termed as connected choice riders) are frustrated with station crowding during the morning peak hours. Conversely, infrequent users - primarily students who live relatively far from the central station - want more off-peak services and better internet connectivity (Grisé & El-Geneidy, 2018).

Table IV-1. Summary of Selected Studies

Study (Year)	Data source and methodology	Variables	Key findings
Studies on rider's satisfaction and perception about transit (USA, Canada, and other countries)			
Wan et al. (2016)	• 1,700 bus rapid transit (BRT) riders of four routes in New York City • 5 points Likert scale survey questions • T-test, chi-square (χ^2) test, and ordinary least squares (OLS) regressions	• BRT variables. 13 key service attributes: frequency, speed, on-time performance, bus-only lanes, signs on off-board ticket machines, shelters, three-door buses, ease of using tickets, bus comfort and cleanliness, route and schedule information, proximity of bus stops, real-time information, limited stops • For OLS, *dependent variable:* total satisfaction; *explanatory variables:* age, gender, weather conditions, weekday vs. weekend service, trip purpose, and satisfaction level of 13 attributes	• Three top service attributes of BRT: frequency, on-time performance, and speed • Two types of riders: BRT dependent and new riders attracted to BRT by better service and accessibility. The former care more about service quality, the latter about comfort and cleanliness. • Travelers, who are young, male, and traveling for purposes other than work and school, use more the schedule information at bus stops and real-time information on the internet
de Oña et al. (2016)	• 3,664 respondents to customer satisfaction surveys (CSS) for bus services conducted by the Transport Consortium of Granada, Spain, between 2008 and 2011. • Cluster analysis and decision tree techniques	• Gender, age, travel reason, frequency of travel, type of ticket, private vehicle availability, complementary modes from origin to bus stop, complementary modes from bus stop to destination • Four clusters of customers. *Cluster 1:* young, frequent trip makers for academic purposes, consortium pass holders, don't own a private vehicle; *Cluster 2:* middle-aged working women, frequent trip makers for jobs, consortium pass holders; *Cluster 3:* women, sporadic users, standard ticket holders; *Cluster 4:* elderly men and women who don't own a private vehicle.	• Overall, customers value frequency, punctuality, speed, safety, and space. However, this varies depending on passenger type • Young passengers prefer service punctuality due to their fixed schedule, and working-class women groups prefer information and service frequency • Passengers with private vehicles value bus speed. For elderly passengers, information plays a central role in choosing a bus service

Grisé & El-Geneidy (2018)	• 4,750 respondents from customer satisfaction survey on the GO rail transit of the Greater Toronto and Hamilton Area (GTHA), Canada, conducted between 2011 and 2016. • Principal component analysis and k means cluster analysis	• 6 broad service attributes: service and train stations (safety, cleanliness, helpfulness, and friendliness of staff, lighting, personal safety in parking lots, temperature on trains, communication of service delays, sufficient fare inspections, availability of seats); loyalty and overall GO train satisfaction (recommend service to others, continue to use service, overall satisfaction and on-time service); accessibility and commuting behavior (number of jobs within accessible distance from GO train stations, commuting distance, train frequency during AM peak); level of service (accessibility to parking); financial status and personal travel behavior (income, employment status and boarding time); satisfaction with parking & parking occupancy	• Seven clusters: loyal underserved users, frustrated yet dedicated riders, young urbanites, spatially captive users, connected choice riders, long-distance commuters, infrequent younger students. • Loyal underserved users have a positive perception of station cleanliness, personnel, and personal safety at train stations, but are unhappy with on-time performance, seat availability and communication of delays • Spatially captive users are satisfied with the availability of parking and seats; • Recommendations: expand park-and-ride at suburban stations, prioritize bicycle facility upgrades at stations, increase off-peak service, and expand network
Zhen et al. (2018)	• Online survey of 851 high-speed rail (HSR) users in Shanghai, China between January 10–24, 2016, and February 24–May 23, 2016. • Multivariate regression and Importance-performance analysis	• *Dependent variable:* passenger's satisfaction • *Explanatory variables:* 17 HSR service attributes; Socioeconomic characteristics: gender, age, education, and income	• Unlike conventional trains (seen as slow, noisy, messy, and smelly), HSR service offers a different experience leading to different preferences: staff attitudes, convenience of ticket purchase, ease of access, and frequency of service.
Sun et al. (2020)	• Self-administered survey data of 742 riders of fixed bus routes in Harbin, China, between May and July 2019. • Linear regression and Importance-performance analysis	• *Dependent variable:* overall passenger satisfaction • *Explanatory variables:* waiting environment attributes: trashcans, shelters, advertisement infrastructure, comfort while waiting, benches, security cameras, lights, signage design, real-time information, safety while waiting	• Trashcans, comfort while waiting, and security cameras are important service attributes for bus stop waiting areas. • Four of the 11 attributes showed non-linear and asymmetric relationships with overall rider satisfaction with the waiting environment.

Covid 19 and transit-related studies in the United States			
Ehsani et al. (2021)	• The Harris Poll panel online Survey of 2,011 U.S. adults; aged ≥18 years • June 17 to 29, 2020 • Descriptive statistics	• Before, during, and after pandemic mobility patterns in urban and suburban areas in the US • Walking, biking, transit, and private car trips	• During the pandemic, total local travel decreased by 10.4%; public transit trips fell by ~23.2%, followed by private cars (13.4%) and walking (10.2%) • No significant changes were observed in bicycle trips; anticipate increase in bicycle use after the pandemic: ~33% in suburban areas and ~10.5% in urban areas
Kim & Kwan (2021)	• Mobility data from 2639 counties based on mobile phone location; • American Community Survey (ACS) 5-years estimates; 2020 Presidential election results; USA Facts, 2020; Oxford COVID-19 Government Response Tracker • Survey period: March to September 2020 • Two waves: 1 (March–June) and 2 (June–September) • Growth model	*Dependent variable:* Monthly average distance (km) covered by an individual in a county, which was termed as mobility *Explanatory variables:* • percentage of residents below poverty, population density, political partisanship, COVID-19 cases per capita, and mobility restrictions in each county.	• Wave 1 results: mobility declined between March and April 2020 and then recovered between April and June. Mobility changes are significantly correlated with political partisanship, poverty level, and the strictness of mobility restriction policies. • Wave 2 results: minor mobility decline despite strict mobility restrictions and more severe COVID cases. Strict mobility restrictions policies during the pandemic somehow had little impact on mobility
Hu & Chen (2021)	• 20 years of daily transit ridership data from Chicago: January 2001 to April 2020 • Chicago Transit Authority (CTA); General Transit Feed Specification (GTFS); Chicago Metropolitan Agency for Planning (CMAP), 2017 American Community Survey (ACS) 5-year estimates; Chicago Data Portal;	• For BSTS: *Dependent variable:* Station level daily average ridership. *Explanatory Variables:* Holiday status, daily maximum temperature, and precipitation • For PTS: *Dependent variable:* Proportion of decrease in ridership caused by COVID-19. *Explanatory variables:* Socio-demographic (Block group): Age, race, median HH income, college degree holders, jobs and population densities, % of jobs in goods/producing and trade/transportation sectors. Land use: % of	• In Chicago, COVID-19 had an impact on ~95% of stations, pulling down transit ridership by 72.4%. • Regions with more white, educated, and high-income people and with more commercial land use lost more transit riders; regions with more trade, transportation, and utility sectors jobs, saw smaller declines.

	LEHD; National Climatic Data Center (NCDC). • Three models: Bayesian Structural Time Series (BSTS) model; inferring impact of COVID 19 and Partial Least Square (PTS) model	commercial land, industrial, institutional, open space, and residential land within a 1 km buffer **COVID 19:** zip code level number of affected cases and deaths until April 30, 2020 Transit Service (Station level): daily # of trips and daily average transit frequency.	• COVID-19 severity: regions with more severe cases/deaths had smaller transit declines
Brough et al. (2021)	• King county, Washington, US • Anonymized geolocated cell phone data from SafeGraph Inc., between February 2020 and April 2020; King County Metro automated passenger counter (APC) • Descriptive Statistics and OLS	• Average number of daily activities (visits to a CBG) in a census block group (CBG) between February-April 2020 • Bus boarding data; ORCA and ORCA LIFT fare data	• The average travel activities declined by 57% in all CBGs. CBGs with a low % of college graduates observed a 45% decline in travel, whereas CBGs with a high % of people with an undergrad education saw more decline • Between February and April, transit boardings dropped by 74%. CBGs with advanced degree holders and affluent residents lost more boardings than others. • Rides from ORCA cardholders plummeted by 51%, whereas ORCA LIFT (households whose income is less than 200% of the federal poverty line) cardholders rides dropped by 32%
Wilbur et al. (2020)	• Nashville and Chattanooga, TN • Data: Metropolitan Government of Nashville and Davidson County; Chattanooga Area Regional Transportation Agency; U.S. Census Bureau and Proximity One • Study period: January 1, 2019, to July 1, 2020. • Descriptive analysis	*Dependent variable:* the average ridership per week *Independent variable:* Median Income, Median Housing Value, • Median Rent, Race	• In Nashville and Chattanooga, ridership declined by 66.9% and 65.1%, respectively, by late April. • Temporal investigation on ridership showed that ridership dropped significantly during the morning and evening peak periods on weekdays, probably due to the stay-at-home orders and remote work options. • Affluent census tract in Nashville lost more riders than less affluent ones.

DeWeese et al. (2020)	• 30 U.S. and 10 Canadian cities • General Transit Feed Specification (GTFS); Statistics Canada; U.S. Census Bureau. • February 2020, April 2020, May 2020 • Descriptive statistics	*Dependent Variable:* stop level changes in service frequency *Independent Variable:* For the U.S.: block group level median household income, % of non-white residents, and % of people without bachelor's degree For Canada: dissemination area level unemployed, % of immigrants within the last five years, and % of households who spend more than 30% of income on rent	• Transit agencies adopted different strategies to address equity issues • Chicago CTA's made fewer service adjustments because transit was predominantly used by essential public service workers and first responders. • Seattle, New York, and Houston made little to substantial service changes with little impact on low-income people in Seattle. • Miami and Riverside cut services extensively across all income groups. • In Canada, Montreal and Toronto implemented service cuts and additions that disproportionally impacted low-income people.

Other Countries

Results from rider satisfaction surveys in other countries echo the findings summarized above for the U.S. and Canada.

After a cluster analysis, de Oña et al. (2016) reported that punctuality is important to younger customers (especially students) because of their fixed class schedules. In contrast, working-class users put more value on information and the frequency of bus services.

The bus stops environment also matters for transit customers outside of the U.S. Indeed, an investigation on the preferences of 724 riders in China showed that while waiting at a bus stop, passengers prefer to have trashcans nearby, value comfort, and would like security cameras inside the bus stop (Sun et al., 2020). In another China study, Zhen et al. (2018) emphasized the importance of evaluating passengers' views about high-speed rail (HSR) services, which are premium high-price services and serve inter-city travel markets. Whereas traditional railway services are often seen as relatively noisy, messy, and smelly, they showed that HSR patrons want a different experience and value staff attitudes, the convenience of ticket purchases, ease of access, toilet cleanliness, reliable Wi-Fi connections, and service frequency.

Additional insights about user satisfaction, perceptions, preferences, attitudes towards bus and rail transit services can be found in other studies summarized in Table **IV-1** (e.g., see de Oña et al., 2016; de Oña et al., 2016; Eboli & Mazzulla, 2011, 2015; Hassan et al., 2013; X. Hu et al., 2015; Machado-León et al., 2016; Zhang et al., 2019).

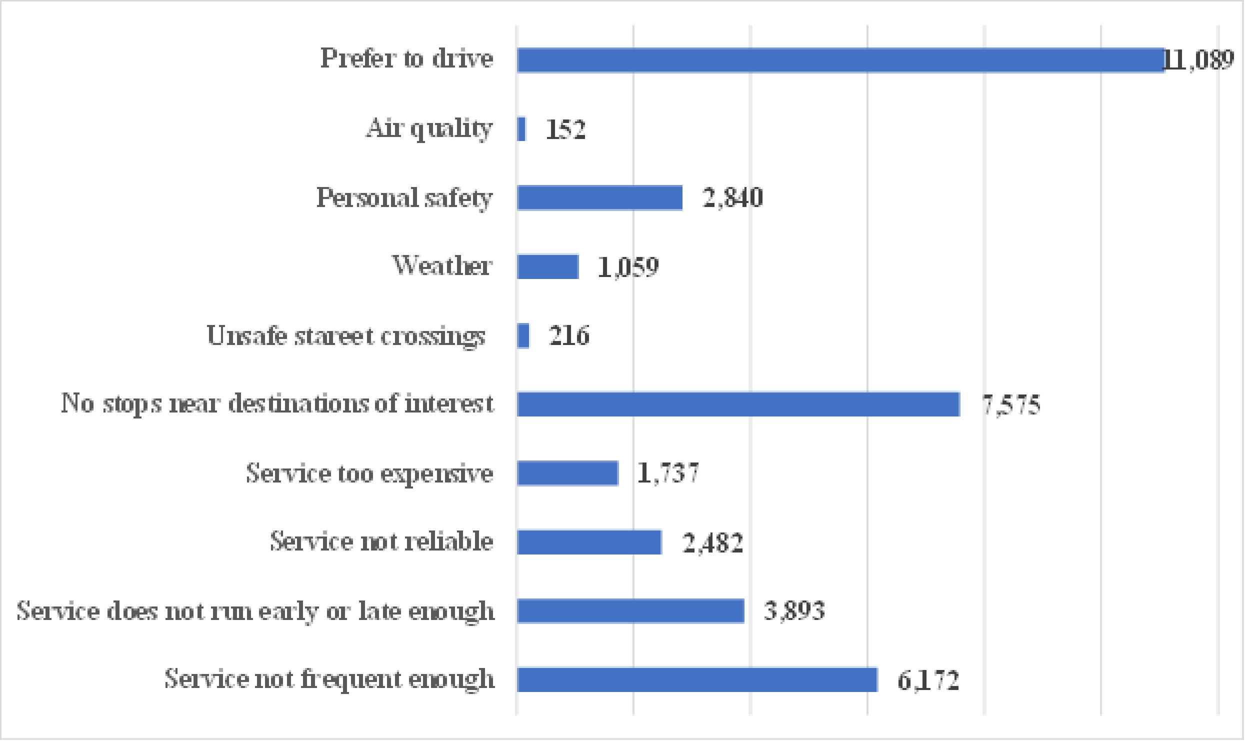
Recent studies also emphasized the implications of COVID-19 on transit ridership (Brough et al., 2021; DeWeese et al., 2020; Ehsani et al., 2021; S. Hu & Chen, 2021; Kim & Kwan, 2021; Wilbur et al., 2020), but to the best of our knowledge, none investigated what would matter most to potential transit riders once the pandemic is over. A summary of the studies we reviewed is presented in Table **IV-1**.

DATA AND MODELS

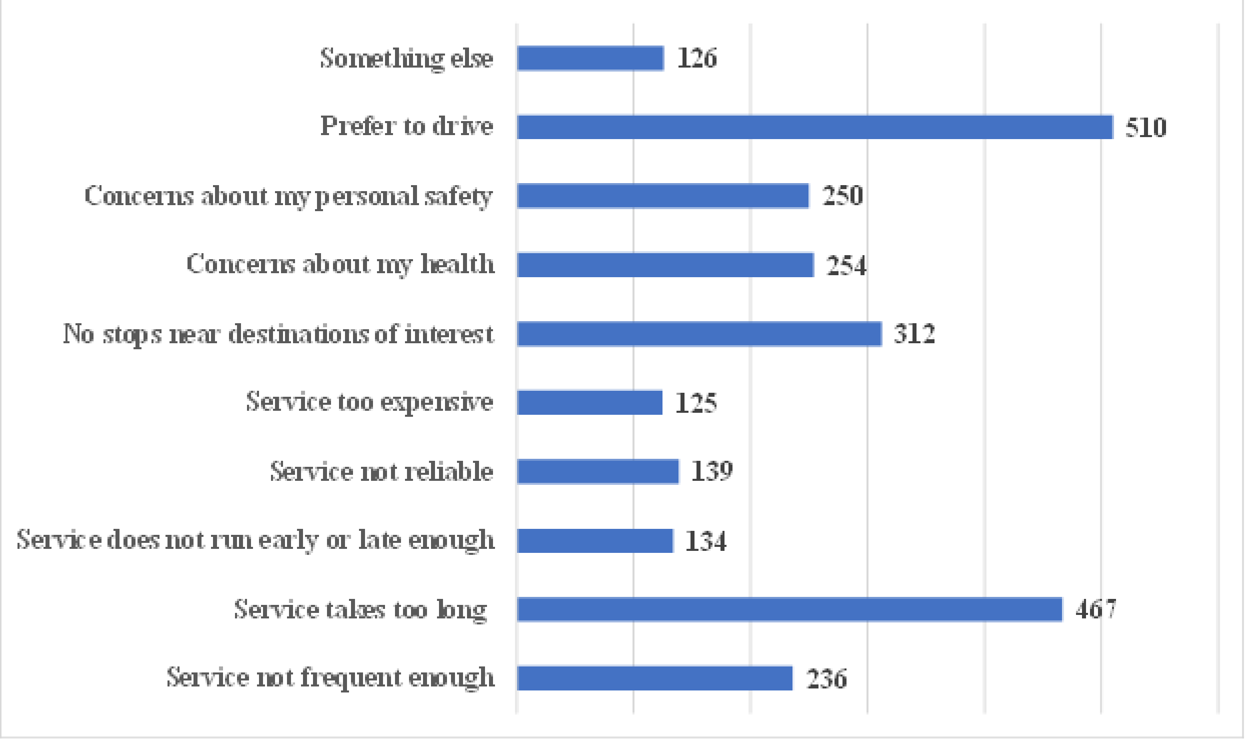
Data

2017 NHTS

As mentioned in previous chapters, data from the 2017 NHTS are organized into four files: person, household, vehicle, and trip files (U.S. Department of Transportation, 2018). In this chapter, we analyzed responses to the question: " What keeps you from taking transit (or taking transit more often) to your destination(s)? Please SELECT THE TOP THREE reasons." It was asked only to California respondents at least 16 years of age. Panel A of Figure IV.1 tallies the number of respondents who selected each reason as one of their top three choices. We see that the main reason is “Prefer to drive” (56.2%), followed by “No stops near destination of interest” (38.4%) and “Service not frequent enough” (31.3%).



Panel A. Reasons for not taking transit more before the pandemic (N=19,734)



Panel B. Reasons for not taking transit more after the pandemic (N = 979)

Figure IV.1. Reasons invoked by Californians for not taking transit more

2021 COVID-19 Survey

As the COVID-19 pandemic is waning out, transit agencies' top priority is winning back riders' trust in transit. Therefore, it is crucial to explore what people think about transit now. To that effect, we analyzed responses to a question about obstacles to taking transit once the pandemic is over in a random survey of Californians conducted by IPSOS in May 2021 for UCI. This survey was administered to California members of KnowledgePanel, which is representative of the California population. Figure III.1 shows the location of respondents to the 2021 Covid-19 survey.

Specifically, we asked, "After the Covid-19 pandemic is over and assuming pre-Covid-19 transit schedules and prices, what would prevent you from taking transit more (local buses, commuter trains, subway, trams, or ferries) for any travel purpose? Please rank your top three reasons (from 1=most important overall to 3=3rd most important)." Responses are summarized on Panel B of Figure IV.1. Again, "Prefer to drive" comes first (52.1%), with "Service takes too long" (47.7%) a close second, followed by "No stops near destination of interest" (31.9%), which was third in the 2017 NHTS question. We also note that three other reasons were also mentioned by roughly a quarter of respondents each: "Concerns about my health" (25.9%), "Concerns about my personal safety" (25.5%), and "Service not frequent enough" (24.1%).

Models and Dependent Variables

For each survey, we analyzed the top three reasons respondents gave for not taking transit (more) using logit models (Train, 2009). For each reason, our dependent variable equals one if a respondent selected that reason in its top three, and 0 otherwise. For each model, we included a rich set of explanatory variables known to impact transit use (see below). In addition, we estimated logit models to understand, once the pandemic is over, which Californians may have health concerns about taking transit or concerns about their personal safety at transit stops or in transit vehicles.

To interpret our results, we relied on odds ratios (Hosmer & Lemeshow, 1991), as is typical for logit models. The odds ratio (OR) is a way of comparing whether the probability of an event (here selecting a reason for not taking transit more) is the same for two groups. The odds of an event is the ratio of the probability that the event will happen (here that a respondent picked a specific reason for not taking transit more) divided by the probability that it will not occur, calculated using the explanatory variables in the logit model. In the odds ratio for explanatory variable j, the odds in the denominator are calculated with the same explanatory variables as the odds in the denominator, except that explanatory variable j is larger by one unit. If the OR for explanatory variable j is around 1 for a reason for not taking transit more, then explanatory variable j has no impact on whether a respondent will not take transit more for that reason; if the OR is greater than one, a respondent is more likely to give that reason for not taking transit more; the reverse holds if OR is lower than one.

Explanatory variables

We selected our explanatory variables based on our literature review, the variables available in the 2017 NHTS dataset, and the data collected from the 2021 COVID-19 survey. We divided our explanatory variables into three categories: individual-specific attributes, household-specific attributes, and land-use variables.

Individual specific attributes

We gathered the following information for each respondent in our sample from the person file: age, gender, race/ethnicity, Hispanic status, educational attainment, occupation, and whether a respondent was born in the U.S.

Many studies have considered age and gender for explaining transit use preferences (de Oña et al., 2016; Wan et al., 2016; Zhen et al., 2018). Therefore, we included age as generation variables (Four binary variables: Generation Z & Y, Generation X, Baby boomers and Silent and GI Generation; baby boomers serve as a baseline) and gender as a binary variable in our model.

The literature also suggests that individual educational attainment and occupation play a pivotal role in transit choice preferences (Clark, 2017; de Oña et al., 2016; Zhen et al., 2018). To capture the level of education of a respondent, we followed the classification used in the 2017 NHTS and created four binary variables: high school or less, some college or associate degree, undergraduate degree (our baseline), and graduate or professional degree.

Similarly, we summarized occupation into five categories: 1) sales and service; 2) clerical or administrative support; 3) manufacturing, construction, maintenance, or farming; 4) professional, managerial, or technical; and 5) others (only for the COVID-19 survey).

Race and Hispanic status play an important role in transit use (Berrebi & Watkins, 2020; Clark, 2017; Taylor & Morris, 2015). Based on the frequency of responses in the 2017 NHTS, we created four binary race variables: Caucasian, African American, Asian, and Other (for options with groups or people claiming a mixed race). Hispanic status was determined similarly. We also created a binary variable to indicate if a respondent was born in the U.S. (only for the 2017 NHTS)

Household specific attributes

Our models also include standard household variables such as annual household income, household size, vehicle ownership, and homeownership, which have been found to matter for explaining household travel preferences (Clark, 2017).

We collapsed the eleven categories in the 2017 NHTS into five binary categories to represent annual household income, with $50,000-$74,999 as our baseline. In addition, for the Covid-19 survey questions, we added four variables that captured the changes in household income during the pandemic (household income increased, decreased, remained unchanged, or the respondent did not know).

We also created a binary variable to code homeownership and a count variable for household members. As the decision to take transit should not depend directly on the number of household vehicles or the number of driver's license holders, but rather on whether a household has more drivers than vehicles, we defined a binary variable that equals one if a household has more drivers than vehicles and 0 otherwise. Since the Covid-19 survey did not ask for the number of household drivers, we created instead three binary variables to indirectly capture changes in mobility restrictions associated with car ownership: the number of household vehicles increased, decreased, or remained unchanged (baseline) during the pandemic compared to before.

Land use variables

Our literature review (Eboli et al., 2018; Grisé & El-Geneidy, 2018) showed the importance of capturing geographical variation in evaluating passenger's perception of transit use. The 2017 NHTS includes some land-use variables commonly included in models of transit ridership. We included two of them in our models: population density (1,000 persons/sq. mile) of the census tract of the household's home location and characteristics of the metropolitan statistical area (MSA) where a household is located (MSA with and without a rail service). For our Covid-19 survey, we defined population density (people/acres) by zip code.

Our literature review also shows that places with more transit facilities, such as transit stops within walking distance, increase people's tendency to walk and take public transit. Therefore, we included in our models the number of transit stops within 500 m of a respondent's home and the same for her/his workplace, which we created using GIS. For our CVOID-19 survey, we also included a variable that captures the number of transit stops near residential home zip codes.

After removing observations with missing variables, our final sample size from the 2017 NHTS is 19,734. We also lost a few observations to missing variables (non-response) in our Covid-19 survey, for which our final sample size is 979. Table IV-2 and Table IV-3 presents descriptive statistics for the explanatory variables used in the logit models presented in this chapter.

Table IV-2. Summary Statistics for 2017 NHTS Variables (N=19,734)

	Mean	Min	Max
Individual specific variables			
Generation			
Generation Z & Y	0.38	0	1
Generation X	0.35	0	1
Baby boomers	0.25	0	1
Silent and GI Generation	0.01	0	1
Gender (Male = 1)	0.52	0	1
Hispanic status (Hispanic =1)	0.15	0	1
Ethnicity			
Caucasian	0.74	0	1
African American	0.03	0	1
Asian	0.11	0	1
Other	0.12	0	1
Educational attainment			
Less than high school & high school	0.15	0	1
Some college or associate degree	0.30	0	1
Undergraduate degree	0.28	0	1
Graduate or professional degree	0.27	0	1
Occupation			
Sales and service	0.22	0	1
Clerical or administrative support	0.11	0	1
Manufacturing, construction, maintenance, or farming	0.11	0	1
Professional, managerial, or technical	0.56	0	1
Not born in the US	0.18	0	1
Household specific variables			
Annual household income			
<$25,000	0.07	0	1
$25,000-$49,999	0.14	0	1
$50,000-$74,999	0.15	0	1
$75,000-$99,999	0.15	0	1
$100,000-$149,999	0.23	0	1
>=$150,000	0.23	0	1
Number of people in the household	2.73	1	11
Household owns home	0.69	0	1
Fewer vehicles than drivers	0.10	0	1
Land use variables			
Household in an MSA with rail service (Yes=1)	0.33	0	1
Population density (1000 persons/sq. miles)	6.95	0.05	30
Number of stops within 500m buffer distance of a household	4.45	1	110
Number of stops within 500m buffer distance of a workplace	8.72	1	131

Table IV-3. Summary statistics for 2021 Covid-19 survey variables (N=979)

	Mean	Min	Max
Individual specific variables			
Generation			
Generation Z & Y	0.26	0	1
Generation X	0.28	0	1
Baby boomers	0.37	0	1
Silent and GI Generation	0.09	0	1
Gender (Male = 1)	0.52	0	1
Hispanic status (Hispanic =1)	0.27	0	1
Ethnicity			
Caucasian	0.74	0	1
African American	0.06	0	1
Asian	0.14	0	1
Other	0.06	0	1
Educational attainment			
Less than high school & high school	0.26	0	1
Some college or associate degree	0.31	0	1
Undergraduate degree	0.25	0	1
Graduate or professional degree	0.18	0	1
Occupation			
Sales and service	0.15	0	1
Clerical or administrative support	0.10	0	1
Manufacturing, construction, maintenance, or farming	0.06	0	1
Professional, managerial, or technical	0.17	0	1
Other	0.09	0	1
Household specific variables			
Annual household income			
<$25,000	0.10	0	1
$25,000-$49,999	0.14	0	1
$50,000-$74,999	0.14	0	1
$75,000-$99,999	0.15	0	1
$100,000-$149,999	0.20	0	1
>=$150,000	0.26	0	1
Number of people in the household	2.78	1	10
Household owns home	0.66	0	1
Changes in household income during the COVID-19			
HH income decreased	0.18	0	1
HH income did not change	0.58	0	1
HH income increased	0.16	0	1
Does not know about HH income change	0.09	0	1
Changes in number of household vehicles during Covid-19			
It decreased	0.04	0	1

It did not change	0.92	0	1
It increased	0.04	0	1
Land use variables			
Household in an MSA with rail service (Yes=1)	0.97	0	1
Population density (1000 persons/acres)	9.17	0	88.8
Number of transit stops in zip code of residence	84.84	1	368

RESULTS AND DISCUSSION

Our logit models were estimated using Stata 15. Results in the form of odds ratios (Hosmer & Lemeshow, 1991) are presented in Table IV-4 for the 2017 NHTS models and Table IV-5 for the 2021 Covid-19 survey models. We discuss them in turn.

Findings from the 2017 NHTS

First reason for not using transit more: I prefer to drive

From Column I of Table IV-4, we see that only a few explanatory variables are statistically significant. Hispanic respondents (OR=1.12*) are more likely to state that they prefer driving over transit. Likewise, as families get larger, they tend to prefer driving over transit (OR=1.07***). Conversely, respondents who hold advanced degrees (OR=0.81***), were not born in the U.S. (OR=0.76***), belong to low-income households (OR=0.85*), and whose household has fewer vehicles than drivers (OR=0.65***), are less likely to state that they simply prefer driving. Finally, we note that the odds ratios for our land-use variables are close to 1, so land use has no practical impact on people's preference for driving over transit.

These results illustrate two important points. First, even though Hispanics and Asians use transit more than Caucasians and Asians (Manville et al., 2018), once available, their priority shifts from transit towards private vehicles. Second, a large fraction of mass transit users is highly educated (Clark, 2017), and their driving preference does not demotivate them to use transit (but we know that they are more likely to use rail transit than buses to commute).

Second reason: No stops near destinations of interest

From Column II of Table IV-4, we see that younger respondents (Gen Z & Y) are more likely to invoke the lack of transit stops as a reason for not taking transit (OR=1.13**), and so do respondents with graduate and professional degrees (OR=1.11*), a higher household income (OR=1.22*** for [$100k, $150k], and OR=1.45*** for >$150k), who live in an MSA with rail (1.31***), and those born elsewhere (OR=1.10*). Some of these findings echo results from the transit literature, where some studies have shown that students and office workers prefer more frequent, on-time, and accessible transit facilities to and from their destinations (de Oña et al., 2016; Grisé & El-Geneidy, 2018).

Table IV-4. Transit Use Reluctance in CA before Covid-19 (N=19,734)

	Y= I prefer to drive	Y=No stops near destinations of interest	Y=Service not frequent enough
Column number →	I	II	III
Individual specific variables			
Generation (Baby boomers = baseline)			
Generation Z & Y	1.04	1.13**	1.20***
Generation X	1.06	0.98	1.08
Silent and GI Generation	0.91	1.14	0.65*
Gender (Male = 1)	1.02	1.00	1.04
Hispanic status (Hispanic =1)	1.12*	0.81***	0.85**
Race (Caucasian = baseline)			
African American	1.09	0.63***	0.73**
Asian	0.99	1.06	1.22***
Other	0.93	0.94	0.98
Educational attainment (Undergraduate degree = baseline)			
Less than high school & high school	1.06	0.74***	0.54***
Some college or associate degree	1.05	0.79***	0.72***
Graduate or professional degree	0.81***	1.11*	1.20***
Occupation (Professional, managerial, or technical = baseline)			
Sales and service	1.00	0.78	0.87
Clerical or administrative support	1.02	0.88	0.96
Manuf., constr., maintenance, or farming	0.93	0.98	0.77
Not born in the USA	0.76***	1.10*	1.29***
Household specific variables			
Annual household income ($50,000-$74,999 = baseline)			
<$25,000	0.85*	0.90	1.01
$25,000-$49,999	0.98	0.84**	1.05
$75,000-$99,999	1.01	1.09	1.15*
$100,000-$149,999	1.00	1.22***	1.12*
>=$150,000	0.99	1.45***	1.20***
Number of people in the household	1.07***	0.95***	0.96**
Household owns home	1.07	1.06	0.95
Fewer vehicles than drivers	0.65***	0.90	1.07
Land use			
Household in an MSA with rail (Yes=1)	1.01	1.31***	0.99
Population density (1000 persons/ mi^2)	1.01***	0.99***	1.00
Number of stops within 500 m of residence	0.98***	0.99***	0.99
Number of stops within 500 m of workplace	0.99***	0.99***	1.00
Constant	1.16*	0.76***	0.49***

1. * p<0.05, ** p<0.01, *** p<0.001. 2. The table above shows the odds ratio (OR) for each explanatory variable.

Table IV-5. Transit Use Reluctance in CA after Covid-19 (N=979)

	I prefer to drive	Service takes too long compared to driving	No stops near destinations of interest	Concerns about my health due to the proximity of many people	Concerns about my personal safety at a transit station or in a transit vehicle
Column number →	I	II	III	IV	V
Individual specific variables					
Generation (Baby boomers = baseline)					
Generation Z & Y	0.76	1.45	1.03	0.99	1.21
Generation X	0.85	1.46*	1.30	0.91	0.79
Silent and GI Generation	0.77	0.72	0.80	0.52	0.35**
Gender (Male = 1)	0.82	1.23	1.27	0.86	0.63**
Hispanic status (Hispanic =1)	0.77	0.53**	0.97	1.53	1.19
Race (Caucasian = baseline)					
African American	0.83	0.53*	0.56	2.11*	0.96
Asian	0.90	1.06	0.71	1.73*	1.75*
Other	0.95	1.13	1.09	1.20	1.18
Educational attainment (Undergraduate degree = baseline)					
Less than high school & high school	1.07	0.77	0.47**	0.93	0.88
Some college or associate degree	1.14	1.01	0.93	0.81	1.05
Graduate or professional degree	0.52**	0.94	1.13	1.24	1.23
Occupation (Professional, managerial, or technical = baseline)					
Sales and service	0.99	0.79	0.81	1.01	0.89
Clerical or administrative support	0.91	1.19	1.05	1.01	0.83
Manufacturing, construction, maintenance, or farming	1.54	0.79	1.34	1.24	0.66
Other	1.20	1.03	0.82	1.03	0.73
Household specific variables					
Annual household income ($50,000-$74,999 = baseline)					
<$25,000	0.74	0.69	0.39*	1.33	0.52

$25,000-$49,999	0.75	1.15	1.01	0.95	0.86
$75,000-$99,999	1.21	1.40	1.29	1.07	0.73
$100,000-$149,999	1.30	1.96**	1.10	1.02	0.94
>=$150,000	1.16	1.63*	1.51	0.81	0.81
Changes in household income during Covid-19 (No change = baseline)					
It decreased	1.30	1.28	1.07	1.05	0.81
It increased	1.33	1.26	0.95	1.44	1.37
Respondent does not know	0.61*	0.56*	0.83	1.23	1.02
Household owns home	1.27	0.78	0.80	1.28	1.40
Number of people in the household	1.03	1.07	0.97	0.89	1.06
Change in the number of HH vehicles before vs. during Covid-19 (No change = baseline)					
It decreased	0.99	0.89	0.52	2.05	1.30
It increased	2.14*	1.58	0.91	0.79	0.72
Land use					
Residence in an MSA with rail (Yes=1)	2.47	2.51*	1.06	1.14	1.05
Population density (persons/acres)	0.99	0.98*	0.97**	1.01	1.01
Number of transit stops in zip code	1.00	1.00	1.00	1.00	1.00

1. * p<0.05, ** p<0.01, *** p<0.001.

2. The values in the table above present odds ratios (OR) of the coefficients of our explanatory variables. An odds ratio greater (lower) than 1 indicates an increased (decreased) likelihood of choosing the corresponding reason for not using transit.

Conversely, Hispanics (OR=0.81***), African Americans (OR=0.63***), respondents with some college or less, and whose annual household income is between $25k and $50k (OR=0.84**) are less likely to mention a lack of transit stops as a reason for not taking transit more, possibly because some of them live in urban cores that are typically served by bus transit.

Finally, we note that except for one land-use variable (households who reside in an MSA with rail service), land-use variables have odds ratios that are close to 1, so they do not play a role in the popularity of this reason for not taking transit.

Third reason: Insufficient service frequency

Many of the explanatory variables that are significant for the lack of transit stops are also significant for service frequency, and they have roughly similar odds ratios (see Column III of Table IV-4). Indeed, younger respondents (Gen Z & Y) are more likely to mention insufficient transit frequency as a reason for not taking transit (OR=1.20**), and so do respondents with graduate and professional degrees (OR=1.20*), a higher household income (OR=1.12*** for [$100k, $150k], and OR=1.20*** for >$150k, but also OR=1.15* for [$75k, $100k]), Asians (OR=1.22***), or those who were born elsewhere (OR=1.29*).

Conversely, older adults (OR=0.65*), Hispanics (OR=0.85***), African Americans (OR=0.73***), and respondents with some college or less, are less likely to mention insufficient service frequency as a reason for not taking transit more. One possible explanation is that older adults may have fewer time constraints. In addition, Hispanics and African Americans may live disproportionately in core urban areas where buses run relatively frequently.

Findings from the 2021 Covid-19 Survey

While interpreting the results below, it is important to remember that our sample size is smaller here (N=979) than for the 2017 NHTS dataset, so our models are not as sensitive.

First reason for not using transit more: I prefer to drive

Starting with Column I in Table IV-5, we see that only a few variables are statistically significant. As before, people with graduate and professional degrees (OR=0.52***) are less likely to state that they prefer driving, possibly because of the flexibility, comfort, and safety that this mode provides. Conversely, and as expected, people whose number of household vehicles increased during the pandemic are more likely to invoke that reason for not considering taking transit after the pandemic (OR=2.14*). Most other variables are not significant, which suggests that the pandemic has solidified the preference for driving versus taking transit among most Californians.

Second reason: Service takes too long compared to driving

The second most popular answer for not taking transit after the pandemic in the Covid-19 survey was “Service takes too long compared to driving.” This reason was not available in the 2017 NHTS. Again, only a handful of variables are statistically significant (see Column II in Table

IV-5). The main result is that the difference in travel time is especially important to Generation X respondents (OR=1.46*), and to people with higher household incomes (OR=1.96** for [$100k, $150k], OR=1.63* for >$150k), which is expected since the value of their time is higher. This result is in sync with previous studies, which have reported that higher-income workers prefer congestion-free, faster travel (Clark, 2017). Conversely, Hispanics (OR=0.53**) and people who are unsure about how their income changed during the pandemic (OR=0.56*) are less likely to mention service time as a reason for not taking transit.

For land use, residing in an MSA with rail (OR=2.51**) increases the likelihood that a respondent is concerned with how long transit takes compared to driving, but other land-use variables do not matter.

Third reason: No stops near destinations of interest

As expected, the lack of transit stops near destinations of interest (Column III of Table IV-5) is a widely shared reason for not taking transit, and it is shared across a broad spectrum of respondents. The only groups less likely to mention this reason are people with a high school education or less (OR=0.47***) and members of households with an annual income below $25,000, two groups that likely overlap.

Fourth reason: Health concerns due to the proximity of many people

Since health concerns have dominated our lives since the start of the Covid-19 pandemic, this question examines if Californians have lingering health concerns that will stop them from taking transit when the pandemic is over. From Column IV in Table IV-5, we see that, after controlling for other socioeconomic variables, African Americans (OR=2.11*) and Asians (OR=1.73**) are more likely than Caucasians (our baseline) to harbor health concerns when taking transit after the pandemic is over. This result confirms a recent survey (Johnson & Funk, 2021), which found that both groups see Covid-19 as more of a threat to public health than Hispanics and Caucasians, combined with the fact that African Americans have been disproportionately affected by that virus. Other variables are not statistically significant.

Fifth reason: Concerns about my personal safety at a transit station or in a transit vehicle

Finally, Column V of Table IV-5 shows the characteristics of Californians more concerned about their personal safety when taking transit. Three variables are statistically significant. First, older Californians (members of the GI and Silent generations) are less concerned about their personal safety in transit than other Californians (OR=0.35**). Second, men are also less concerned about their safety while taking transit (OR=0.63**). This tells us this is more of a concern for women, which is a chronic problem for transit (Loukaitou-Sideris, 2014, 2015; Loukaitou-Sideris & Fink, 2009; Lubitow et al., 2020).

CONCLUSIONS

For this task, we examined the main reasons why Californians were reluctant to use transit in 2017, and why they may be once the Covid-19 pandemic is over. For that purpose, we estimated logit models to tease out the characteristics of those who invoked these reasons.

The main reason why Californians would not take transit before the pandemic and why they likely will not take it after is well-known: Californians prefer to drive, which we interpret as saying that driving a personal vehicle offers more flexibility (e.g., to drive someone, to carry shopping, to leave at any time) and is perceived as safer than taking transit. The second and the third most popular reasons in the 2017 NHTS ("no stops near destinations of interest" and "service not frequent enough") and in our 2021 Covid-19 survey ("no stops near destination of interest," and "service takes too long") reinforce that point.

Our results indicate that limitations of transit's reach and frequency are especially of concerns for younger adults (Gen Z and Gen Y), people with more education, and especially members of more affluent households (the so-called "choice riders"; see (Polzin et al., 2000; Krizek & El-Geneidy, 2007). A key priority for transit agencies should therefore be to increase (as much as possible and appropriate) the frequency of their service, develop their network and extend their reach by addressing the first- and last-mile problems.

To attract younger riders in urban areas, one possibility would be to either offer micro-mobility services (e.g., shared e-scooters, bikes, or e-bikes) or create a partnership with one or several providers. Other measures include enhancing transfers between different transit modes or different transit providers, streamlining payment via smartphone apps (and including micromobility payments), and providing internet service in areas with blank spots.

To address health concerns of African American and Asian riders after the Covid-19 pandemic finally subsides, transit operators should adopt best practices to promote health (many have already done so in California; see Bernstein et al., 2021, for example) and publicize their efforts using both more traditional (e.g., radio and TV ads) and more modern (e.g., social media) approaches.

It is also essential to address public safety concerns, which tend to be voiced by women (Loukaitou-Sideris, 2014, 2015; Loukaitou-Sideris & Fink, 2009; Lubitow et al., 2020) but that are likely shared by many people who are not taking transit. Possible measures include providing adequate lighting at transit stations (especially bus stops), providing a clean and comfortable environment, and possibly installing CCTV cameras. Public acceptance should also be gauged for installing monitoring cameras in transit vehicles, coupled with patrols by public safety officers (considering that policing is a very sensitive issue, especially in disadvantaged communities and communities of color, that have long been singled out by local police officers).

Overall, however, transit policy needs to be integrated into comprehensive policies designed to achieve California's transportation, social, and environmental goals. These policies should consider the generalized costs and the characteristics of all the transportation options available to residents of specific communities. This includes better pricing urban spaces (i.e., parking), and the externalities of private motor vehicles (e.g., air pollution and greenhouse gas emissions), and fostering new mobility options to achieve more equitable mobility.

Finally, we would like to underscore the need for rigorous research on transit issues, especially for small transit agencies in California.

REFERENCES

Bernstein, R., LaBatt, S., & Sektnan, C. (2021). *Bay area transit transformation action plan* (Issue July). https://mtc.ca.gov/sites/default/files/documents/2021-09/Transit_Action_Plan.pdf

Berrebi, S. J., & Watkins, K. E. (2020). Who's ditching the bus? *Transportation Research Part A: Policy and Practice*, *136*(February), 21–34. https://doi.org/10.1016/j.tra.2020.02.016

Brough, R., Freedman, M., & Phillips, D. C. (2021). Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. *Journal of Regional Science*, *June*. https://doi.org/10.1111/jors.12527

Caltrans. (2021). *California Transportation Plan (CTP) 2050*. https://dot.ca.gov/-/media/dot-media/programs/transportation-planning/documents/ctp-2050-v3-a11y.pdf

Carrel, A., Mishalani, R. G., Sengupta, R., & Walker, J. L. (2016). In Pursuit of the Happy Transit Rider: Dissecting Satisfaction Using Daily Surveys and Tracking Data. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *20*(4), 345–362. https://doi.org/10.1080/15472450.2016.1149699

Clark, H. M. (2017). Who rides public transportation. In *American Public Transportation Association*. https://www.apta.com/resources/reportsandpublications/Documents/APTA-Who-Rides-Public-Transportation-2017.pdf

de Oña, J., de Oña, R., Diez-Mesa, F., Eboli, L., & Mazzulla, G. (2016). A composite index for evaluating transit service quality across different user profiles. *Journal of Public Transportation*, *19*(2), 128–153. https://doi.org/10.5038/2375-0901.19.2.8

de Oña, J., de Oña, R., Eboli, L., Forciniti, C., & Mazzulla, G. (2016). Transit passengers' behavioral intentions: the influence of service quality and customer satisfaction. *Transportmetrica A: Transport Science*, *12*(5), 385–412. https://doi.org/10.1080/23249935.2016.1146365

de Oña, J., de Oña, R., & López, G. (2016). Transit service quality analysis using cluster analysis and decision trees: a step forward to personalized marketing in public transportation. *Transportation*, *43*(5), 725–747. https://doi.org/10.1007/s11116-015-9615-0

DeWeese, J., Hawa, L., Demyk, H., Davey, Z., Belikow, A., & El-geneidy, A. (2020). A Tale of 40 Cities: A Preliminary Analysis of Equity Impacts of COVID-19 Service Adjustments across North America. *TRANSPORT FINDINGS*, 1–7. https://doi.org/10.32866/001c.13395

Eboli, L., Forciniti, C., & Mazzulla, G. (2018). Spatial variation of the perceived transit service quality at rail stations. *Transportation Research Part A: Policy and Practice*, *114*(February), 67–83. https://doi.org/10.1016/j.tra.2018.01.032

Eboli, L., & Mazzulla, G. (2011). A methodology for evaluating transit service quality based on subjective and objective measures from the passenger's point of view. *Transport Policy*, *18*(1), 172–181. https://doi.org/10.1016/j.tranpol.2010.07.007

Eboli, L., & Mazzulla, G. (2015). Relationships between rail passengers' satisfaction and service quality: a framework for identifying key service factors. *Public Transport*, *7*(2), 185–201. https://doi.org/10.1007/s12469-014-0096-x

Ehsani, J. P., Michael, J. P., Duren, M. L., Mui, Y., & Porter, K. M. P. (2021). Mobility Patterns Before, During, and Anticipated After the COVID-19 Pandemic: An Opportunity to Nurture Bicycling. *American Journal of Preventive Medicine*, *60*(6), e277–e279. https://doi.org/10.1016/j.amepre.2021.01.011

Fan, Y., Guthrie, A., & Levinson, D. (2016). Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transportation Research Part A: Policy and Practice*, *88*, 251–264. https://doi.org/10.1016/j.tra.2016.04.012

Ge, Y., Knittel, C., MacKenzie, D., & Zoepf, S. (2016). Racial and Gender Discrimination in Transportation Network Companies. *National Bureau of Economic Research*. https://doi.org/10.3386/w22776

Grisé, E., & El-Geneidy, A. (2018). Where is the happy transit rider? Evaluating satisfaction with regional rail service using a spatial segmentation approach. *Transportation Research Part A: Policy and Practice*, *114*(November 2017), 84–96. https://doi.org/10.1016/j.tra.2017.11.005

Hassan, M. N., Hawas, Y. E., & Ahmed, K. (2013). A multi-dimensional framework for evaluating the transit service performance. *Transportation Research Part A: Policy and Practice*, *50*, 47–61. https://doi.org/10.1016/j.tra.2013.01.041

Hosmer, D. W., & Lemeshow, S. (1991). Applied Logistic Regression. In *Biometrics* (Vol. 47, Issue 4). https://doi.org/10.2307/2532419

Hu, S., & Chen, P. (2021). Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership. *Transportation Research Part D: Transport and Environment*, *90* (December 2020), 102654. https://doi.org/10.1016/j.trd.2020.102654

Hu, X., Zhao, L., & Wang, W. (2015). Impact of perceptions of bus service performance on mode choice preference. *Advances in Mechanical Engineering*, *7*(3), 1–11. https://doi.org/10.1177/1687814015573826

Johnson, C., & Funk, C. (2021). *Black Americans stand out for their concern about COVID-19; 61% say they plan to get vaccinated or already have*. Pew Research Center. https://www.pewresearch.org/fact-tank/2021/03/09/black-americans-stand-out-for-their-concern-about-covid-19-61-say-they-plan-to-get-vaccinated-or-already-have/?utm_content=buffer3d0d8&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer

Kim, J., & Kwan, M. P. (2021). The impact of the COVID-19 pandemic on people's mobility: A longitudinal study of the U.S. from March to September of 2020. *Journal of Transport Geography*, *93*(December 2020), 103039. https://doi.org/10.1016/j.jtrangeo.2021.103039

Krizek, K., & El-Geneidy, A. (2007). Segmenting Preferences and Habits of Transit Users and Non-Users. *Journal of Public Transportation*, *10*(3), 71–94. https://doi.org/10.5038/2375-0901.10.3.5

Lagune-Reutler, M., Guthrie, A., Fan, Y., & Levinson, D. (2016). Transit stop environments and waiting time perception: Impacts of trees, traffic exposure, and polluted air. *Transportation Research Record*, *2543*(2543), 82–90. https://doi.org/10.3141/2543-09

Loukaitou-Sideris, A. (2014). Fear and safety in transit environments from the women's perspective. *Security Journal*, *27*(2), 242–256. https://doi.org/10.1057/sj.2014.9

Loukaitou-Sideris, A. (2015). Intimidated Riders: US Women's Perspectives about Safety in Transit Settings. In V. Ceccato & A. Newton (Eds.), *Safety and Security in Transit Environments* (1st ed., pp. 291–308). Palgrave Macmillan. https://doi.org/10.1057/9781137457653

Loukaitou-Sideris, A., & Fink, C. (2009). Addressing women's fear of victimization in transportation settings: A survey of U.S. transit agencies. In *Urban Affairs Review* (Vol. 44, Issue 4). https://doi.org/10.1177/1078087408322874

Lubitow, A., Abelson, M. J., & Carpenter, E. (2020). Transforming mobility justice: Gendered harassment and violence on transit. *Journal of Transport Geography*, *82*(November 2019), 102601. https://doi.org/10.1016/j.jtrangeo.2019.102601

Machado-León, J. L., de Oña, R., & de Oña, J. (2016). The role of involvement in regards to public transit riders' perceptions of the service. *Transport Policy*, *48*, 34–44. https://doi.org/10.1016/j.tranpol.2016.02.014

Malalgoda, N., & Lim, S. H. (2019). Do transportation network companies reduce public transit use in the U.S.? *Transportation Research Part A: Policy and Practice*, *130*(October), 351–372. https://doi.org/10.1016/j.tra.2019.09.051

Manville, M., Taylor, B. D., & Blumenberg, E. (2018). *Falling Transit Ridership: California and Southern California*. https://escholarship.org/uc/item/0455c754

Park, K., Farb, A., & Chen, S. (2021). First-/last-mile experience matters: The influence of the built environment on satisfaction and loyalty among public transit riders. *Transport Policy*, *112*(July), 32–42. https://doi.org/10.1016/j.tranpol.2021.08.003

Polzin, S. E., Chu, X., & Rey, J. R. (2000). Density and captivity in public transit success: Observations from the 1995 nationwide personal transportation study. *Transportation Research Record*, *1735*, 10–18. https://doi.org/10.3141/1735-02

Sun, S., Fang, D., & Cao, J. (2020). Exploring the asymmetric influences of stop attributes on rider satisfaction with bus stops. *Travel Behaviour and Society*, *19*(October 2019), 162–169. https://doi.org/10.1016/j.tbs.2020.01.004

Taylor, B. D., Blumenberg, E., Wasserman, J., & Garrett, M. (2020). *Why is Public Transit Falling in the San Francisco Bay Area , and What Might be Done About It ?* https://escholarship.org/uc/item/7zt9k47v

Taylor, B. D., Blumenberg, E., Wasserman, J., Garrett, M., Schouten, A., King, H., Paul, J., & Ruvolo, M. (2020). *Transit Blues in the Golden State: Analyzing Recent California Ridership Trends*.

Taylor, B. D., & Morris, E. A. (2015). Public transportation objectives and rider demographics: are transit's priorities poor public policy? *Transportation*, *42*(2), 347–367. https://doi.org/10.1007/s11116-014-9547-0

Toussaint, B. Y. K. (2020, May). Post-pandemic public transit may not end up looking all that different — but its goals may have to change. *Fast Company*, 1. https://www.fastcompany.com/90510287/post-pandemic-public-transit-may-not-end-up-

looking-all-that-different-but-its-goals-may-have-to-change
Train, K. E. (2009). Discrete choice methods with simulation, second edition. In *Discrete Choice Methods with Simulation, Second Edition* (Vol. 9780521766). https://doi.org/10.1017/CBO9780511805271
U.S. Department of Transportation. (2018). *2017 NHTS Data User Guide* (Vol. 2018, Issue 301). https://nhts.ornl.gov/assets/2017UsersGuide.pdf
Wan, D., Kamga, C., Hao, W., Sugiura, A., & Beaton, E. B. (2016). Customer satisfaction with bus rapid transit: a study of New York City select bus service applying structural equation modeling. *Public Transport*, *8*(3), 497–520. https://doi.org/10.1007/s12469-016-0135-x
Wan, D., Kamga, C., Liu, J., Sugiura, A., & Beaton, E. B. (2016). Rider perception of a "light" Bus Rapid Transit system - The New York City Select Bus Service. *Transport Policy*, *49*, 41–55. https://doi.org/10.1016/j.tranpol.2016.04.001
Wilbur, M., Ayman, A., Ouyang, A., Poon, V., Kabir, R., Vadali, A., Pugliese, P., Freudberg, D., Laszka, A., & Dubey, A. (2020). Impact of COVID-19 on Public Transit Accessibility and Ridership. *ArXiv Preprint ArXiv:2008.02413.* http://arxiv.org/abs/2008.02413
Wu, X., (Jason) Cao, X., & Ding, C. (2020). Exploring rider satisfaction with arterial BRT: An application of impact asymmetry analysis. *Travel Behaviour and Society*, *19*(December 2019), 82–89. https://doi.org/10.1016/j.tbs.2019.12.006
Wu, X., Cao, J., & Huting, J. (2018). Using three-factor theory to identify improvement priorities for express and local bus services: An application of regression with dummy variables in the Twin Cities. *Transportation Research Part A: Policy and Practice*, *113*(September 2017), 184–196. https://doi.org/10.1016/j.tra.2018.04.003
Zhang, C., Cao, X., Nagpure, A., & Agarwal, S. (2019). Exploring rider satisfaction with transit service in Indore, India: an application of the three-factor theory. *Transportation Letters*, *11*(8), 469–477. https://doi.org/10.1080/19427867.2017.1398484
Zhen, F., Cao, J., & Tang, J. (2018). Exploring correlates of passenger satisfaction and service improvement priorities of the Shanghai-Nanjing High Speed Rail. *Journal of Transport and Land Use*, *11*(1), 559–573. https://doi.org/10.5198/jtlu.2018.958

DATA MANAGEMENT PLAN

This research analyzed data from the 2017 National Household Travel Survey (NHTS) and from a survey of Californians conducted by IPSOS for this project. The 2017 NHTS dataset is publicly available at: https://nhts.ornl.gov/downloads. The second dataset (from the May 2021 survey of Californian in KnowledgePanel®) is the intellectual property of Caltrans. Caltrans will provide public access to the data in December of 2023 with a report describing the different variables. There are no restrictions on how these data can be reused and redistributed by the public, except for an acknowledgement of the origin and the funding agencies (PSR UTC and Caltrans). A copy of the questionnaire is available in the appendix.

APPENDIX: IPSOS survey questionnaire

Study Information

Note: The study information below should be completed for all projects. Copy/paste the tableinto the internal project kickoff meeting invitation so all teams have it for reference.

Client	UCI
Project Name	The Impact of COVID-19 on commuting and shopping in California
Account Executive	Sergei Rodkin
Project Manager	Ying Wang
Ipsos Job Number	21-025657-01
SNO(s)	24064
LOI	12
Type of Study	Ad-hoc, one shot
Field Start Date (tentative is fine)	
Field End Date (tentative is fine)	
Teams Involved	Scripting, Stats
DP Team Scope	NA
Kickoff Meeting Date (tentative is fine)	
Comments	

Sample Variables

- KP standard demographics
- Xspanish (1=English; 2=Spanish)
- Xacslang (1=English Dominant; 2=Bilingual; 3=Spanish Dominant; 4=Hispanic missing data; 5=Non-Hispanic)
- Xzip
- Xcu2: 1=Completed CU2; 2=Not completed
- Xretail: 1= Completed retail; 2=Not completed

Quota Description

The survey sample will target the following population: General population adults, age 18+, English and Spanish language survey-takers, California residents.

- An initial pretest of twenty-five (25) completed interviews.
- A total of one thousand (1,000) completed interviews from the Main Study from KnowledgePanel®.

Main Questionnaire (including screener, if applicable)

Programming Notes:

- *Code all refusals as -1.*
- *Remove default instructions.*
- *Add default instruction for MP questions*
- *Do not prompt on all questions. (Remove this instruction if sample is all opt-in, client list sample, or otherwise not KP.)*

Main survey

Base: all respondents

DISP1 [DISP]

This survey is conducted on behalf of the Institute of Transportation Studies at the University of California, Irvine, with funding from the State of California and from Caltrans. The main purpose of this survey is to understand how COVID-19 has impacted

1) Your travel to work (commuting); and
2) Your in-store and online shopping habits for groceries and meals.

Completing this survey should take **between 8 and 14 minutes of your time**. It has two parts:

- **Part I** asks questions about the impact of COVID-19 on your employment and, if appropriate, how you commute to work.
- **Part II** asks questions about the impact of COVID-19 on your food purchases, including groceries and meals (both in-store and online).

Your responses are very important to help us understand how the Covid-19 pandemic has affected your everyday life.

Thank you for taking the time to complete our survey. Your responses will be kept strictly confidential and will be used for academic purposes only. Your participation is very important for the success of our research.

Base: all respondents

DISP2 [DISP]

In this survey, we distinguish between the period **before the March 2020 stay-at-home Executive Order from Governor Newsom** (just before the pandemic), and the period between **March 2020 and March 2021** (during the pandemic).

We call "household" a group of "people who live together and share at least some financial resources (housemates/roommates are not considered members of the same household)". Motor vehicles are cars, vans, pick-ups, SUVs, mopeds, and motorbikes.

PROGRAMMING NOTE: FOR ALL QUESTIONS IN THIS PART (**QI.1 TO QI.16A_W**), PLEASE ADD A HEADER THAT SAYS: "Part 1: Impact of Covid-19 on your commute to work".

Base: all respondents

First, we would like to ask you about your home location so we can incorporate information about land use in your area into our statistical models.

QI.1 [S]

Did you move since March 2020?

1. Yes
2. No

Base: QI.1=1

QI.1B [N, RANGE 0-99999]

At the beginning of 2020 but before the March 2020 stay-at-home Executive Order from Governor Newsom, what was the ZIP code of your home location?

PROGRAMMER: PROMPT ONCE IF REFUSED, TERMINATE IF ZIP CODE IS NOT IN CALIFORNIA

Base: all respondents

QI.2D [N, RANGE 0-99999]

What is the zip code of your **current** home location?

PROGRAMMER: PROMPT ONCE IF REFUSED, TERMINATE IF ZIP CODE IS NOT IN CALIFORNIA
If zip code NE xzip, use crosswalk to compute MSACAT

Base: all respondents

We would now like to understand your employment situation, and if applicable, characteristics of your journey to work (your commute).

QI.3D [M]

At the end of March 2021, what was your employment situation? Please check all that applies.

1. Homemaker/unpaid caregiver.
2. Employed full time.
3. Employed part time.
4. Furloughed with pay from previous job.
5. Furloughed without pay from previous job.
6. Self-employed.
7. I worked less on average than before the Covid-19 pandemic.
8. I worked more on average than before the Covid-19 pandemic.
9. Retired.
10. Unemployed.
11. Other - Please explain: **[TEXT BOX]**

Base: QI.3D=2, 3, 4, 5, 6, 7 or 8

QI.4D [N, RANGE 0-7]

Between March 2020 and March 2021 (during the pandemic), how many days per week on average (if any) did you work from home?

[NUM BOX] days

Base: QI.3D=2, 3, 4, 5, 6, 7, or 8

QI.5D [S]

Between March 2020 and March 2021 (during the pandemic), did you (at least a few days every month) commute/travel to a workplace location that is not your residence?

1. Yes
2. No

In the questions that follow, we call this work location “your workplace”.

Base: QI.5D=1

QI.6D [S]

Between March 2020 and March 2021, how many days per week on average did you commute from home to your workplace? Please select one option.

1. Once a week or less
2. 2 to 3 times
3. 4 to 5 times
4. More than 5 times a week
5. Other. Please explain: **[TEXT BOX]**

Base: QI.5D=1

QI.7D [S]

Between March 2020 and March 2021, what was the <u>primary</u> mode of transport you typicallyused when commuting from home to work? Please select one option.

1. Drive alone.
2. Carpool.
3. Uber, Lyft, UberPool, LyftLine, or similar.
4. Public transportation (e.g., bus, train, or subway)
5. Bike / walk / scooter.
6. Other – Please explain: **[TEXT BOX]**

Base: QI.5D=1

QI.8D [N, RANGE 0-1440]

On a typical day between March 2020 and March 2021, what was your <u>one-way</u> travel time (door to door) between your home and your workplace?

[NUM BOX] minutes

Base: QI.5D=1

QI.9D [N, RANGE 0-99999]

Between March 2020 and March 2021, what was the zip code of your primary place of work?

[S] Other (please explain): **[TEXT BOX]**

We are asking so we can add land use information into our statistical models.

Base: all respondents

We would now like to ask you about your employment situation and your commute (if applicable) **at the beginning of 2020 but before the March 2020 stay-at-home Executive Order from Governor Newsom.**

QI.3B [M]

At the beginning of 2020 but before the March 2020 stay-at-home Executive Order from Governor Newsom, what was your employment situation? Please check all that applies.

1. Homemaker/unpaid caregiver.
2. Employed full time.
3. Employed part time.
4. Self-employed.
5. Retired.
6. Unemployed.
7. Other - Please explain: **[TEXT BOX]**

Base: QI.3B=2, 3, or 4

The questions below are for the beginning of 2020 but before the March 2020 stay-at-home Executive Order from Governor Newsom, which we consider to be just before the Covid-19 pandemic.

QI.4B [N, RANGE 0-7]

Just before the pandemic, how many days per week on average did you work from home?

[NUM BOX] days

PROGRAMNING NOTE: SHOW "**The questions below are for the beginning of 2020 but before the March 2020 stay-at-home Executive Order from Governor Newsom (just before the pandemic)**." FOR **QI.5B TO QI.9B.**

Base: QI.3B=2, 3, or 4

QI.5B [S]

Just before the pandemic, did you (at least a few days every month) commute/travel to a workplace location that is not your residence?

1. Yes
2. No

In the questions that follow, we call this work location "your workplace".

Base: QI.5B=1

QI.S [ACCORDION]

Did any of the following characteristics of your commute change between the beginning of 2020 (just before the pandemic), and the period between March 2020 and March 2021 (duringthe pandemic)?

Statements:

a. The average number of days per week you went to your workplace
b. Your primary mode of transport to commute to your workplace

c. Your average commute time
d. The location of your workplace

Scales:
1. Yes
2. No

Base: QI.SA=1

QI.6B [S]

Just before the pandemic, how many days per week on average did you commute from hometo your workplace?

1. Once a week or less
2. 2 to 3 times
3. 4 to 5 times
4. More than 5 times a week
5. Other. Please explain: **[TEXT BOX]**

Base: QI.SB=1

QI.7B [S]

Just before the pandemic, what was the primary mode of transport you typically used when commuting from home to your workplace?

1. Drive alone.
2. Carpool.
3. Uber, Lyft, UberPool, LyftLine, or similar.
4. Public transportation (e.g., bus, train, or subway)
5. Bike / walk / scooter.
6. Other – Please explain: **[TEXT BOX]**

Base: QI.SC=1

QI.8B [N, RANGE 0-1440]

Just before the pandemic, what was the average one-way travel time (door to door) between your home and your workplace?

[NUM BOX] minutes

Base: QI.SD=1

QI.9B [N, RANGE 0-99999]

Just before the pandemic, what was the zip code of your primary place of work?

[S] Other (please explain): **[TEXT BOX]**

We are asking to add land use information into our statistical models.

Base: all respondents

QI.10A [N, RANGE 0-7]

After the Covid-19 pandemic is over (when there are no more cases in the U.S.), how many days per week on average do you think you will be working from home?

[NUM BOX] days

Base: all respondents

We would now like to know if the number of vehicles in your household changed since the beginning of 2020, and how the Covid-19 pandemic impacted your household income.

QI.11 [S]

Did the number of motor vehicles (cars, vans, pick-ups SUVs, mopeds, and motorbikes) your household owns or leases change between March 2020 and March 2021 compared to just before March 2020?

1. Yes
2. No

Base: QI.11=1

QI.12B [N, RANGE 0-99]

How many motor vehicles (cars, vans, pick-ups, SUVs, moped, and motorbikes) did your household own or lease just before the March 2020 stay-at-home order from Governor Newsom?

[NUM BOX] motor vehicles

Base: all respondents

QI.12D [N, RANGE 0-99]

At the end of March 2021, how many motor vehicles (cars, vans, pick-ups SUVs, mopeds, and motorbikes) did your household own or lease?

[NUM BOX] motor vehicles

Base: all respondents

QI.13 [S]

Taking into account stimulus checks from the government, what was the impact of the Covid-19 pandemic on your annual household income between March 2020 and March 2021 compared to just before March 2020?

1. It decreased by more than $25,000.
2. It decreased by $10,000 to $24,999.
3. It decreased by up to $10,000.
4. It is roughly unchanged.
5. It increased by up to $10,000.

6. It increased by more than $10,000.
7. I don’t know.

Base: all respondents

DISP3 [DISP]

Finally, we would like to know how the Covid-19 pandemic may have changed your use ofdifferent transportation modes for any travel purpose.

In the next few questions, when we say that the Covid-19 pandemic is over, we mean that there are no more Covid-19 cases in the U.S.

Base: all respondents

QI.14A [ACCORDION]

After the Covid-19 pandemic is over, how often do you think you will be using the following modes for any travel purpose compared to before the Covid-19 pandemic?

Statement:

a. Driving
b. Transit
c. Walking
d. Biking
e. Uber/Lyft
f. UberPool/LyftLine

Scales:

1. Less than before Covid-19
2. Same as before Covid-19
3. More than before Covid-19

Base: all respondents

QI.15A [RANKING, RANGE 1-3]

After the Covid-19 pandemic is over and assuming pre-Covid-19 transit schedules and prices, what would prevent you from taking transit more (local buses, commuter trains, subway, trams, or ferries) for any travel purpose?

Please rank your top three reasons (from 1=most important overall to 3=3rd most important):

[NUM BOX] Service not frequent enough
[NUM BOX] Service takes too long compared to driving
[NUM BOX] Service does not run early or late enough **[NUM BOX]** Service not reliable
[NUM BOX] Service too expensive
[NUM BOX] No stops near destinations of interest
[NUM BOX] Concerns about my health due to the proximity of many people

[NUM BOX] Concerns about my personal safety at a transit station or in a transit vehicle
[NUM BOX] Prefer to drive
[NUM BOX] Something else. Please explain: **[TEXT BOX]**
[S] No other choices apply
[S] I don't know / Prefer not to answer

Base: QI.14A_c or QI.14A_d=1 or 2

QI.16A_W [RANKING, RANGE 1-3]
After the Covid-19 pandemic is over, which of the following will prevent you from walking/biking more for any travel purpose compared to before the Covid-19 pandemic?

Please rank your top three reasons (from 1=most important overall to 3=3rd most important):

Your ranking:

[NUM BOX] Personal health issues
[NUM BOX] No one to walk/bike with
[NUM BOX] No nearby paths or trails
[NUM BOX] No sidewalks / sidewalks narrow or in poor condition
[NUM BOX] Safety concern (crime related)
[NUM BOX] Too much traffic
[NUM BOX] Air quality
[NUM BOX] Something else. Please explain: **[TEXT BOX]**
[S] No other choices apply
[S] I don't know / Prefer not to answer

Base: all respondents

DISP4 [DISP]
Part 2. This part asks questions related to your household's food purchases (grocery and prepared meals) before, during, and after the Covid-19 pandemic.

First, we would like to ask you a few questions about your household's shopping habits for groceries and for prepared meals **before** the **March 2020 stay-at-home Executive Order from Governor Newsom**.

PROGRAMMING NOTE: FOR ALL QUESTIONS IN THIS PART (**QII.1B TO QII.4A**), PLEASE ADD A HEADER THAT SAYS: "Part 2: Impact of Covid-19 on your food purchases".

Base: all respondents

QII.1B. [ACCORDION]
Before the **March 2020 stay-at-home Executive Order from Governor Newsom**, how often did your household use the following grocery shopping options?

Statement:

a. **In person grocery shopping** in a brick-and-mortar store or a farmers market
b. **Online purchase of groceries with home delivery** (e.g., via Amazon Fresh, Instacart, or Costco grocery)
c. **Online order of groceries with store pick-up** (via drive-thru, in-store pickup, or curbside pickup)
d. Other. Please briefly describe: **[TEXT BOX]**

Scales:

1. Never
2. Occasionally but less than once a month
3. 1-3 times a month
4. 1-2 times a week
5. 3 or more times a week
6. I do not know

Base: all respondents

QII.2B. **[ACCORDION]**

In the few months **before** the **March 2020 stay-at-home Executive Order** from Governor Newsom, how often did your household get take-out food or ordered food online and had it delivered?

Statement:

a. **Eat on site** (at a restaurant, café, fast food, or food court)
b. **Take-out food** (e.g., drive-thru, click & collect, in-person pickup, or curbside pickup)
c. **Online food order with delivery** (via DoorDash, Grubhub, Postmates, UberEats, or similar)

Scales:

1. Never
2. Occasionally but less than once a month
3. 1-3 times a month
4. 1-2 times a week
5. 3 or more times a week
6. I do not know

Base: all respondents

DISP5 [DISP]

Now, we would like to ask you a few questions about your household's shopping habits for groceries and for prepared meals <u>since</u> the **March 2020 stay-at-home Executive Order from Governor Newsom**.

Base: all respondents

QII.1D. **[ACCORDION]**

<u>Since</u> the **March 2020 stay-at-home Executive Order from Governor Newsom**, how often has your household used the following grocery shopping options?

Statement:

a. **In-person grocery shopping** in a brick-and-mortar store or a farmers market
b. **Online purchase of groceries with home delivery** (e.g., via Amazon Fresh, Instacart, or Costco grocery)
c. **Online order of groceries with store pick-up** (via drive-thru, in-store pickup, or curbside pickup)
d. **Other.** Please briefly describe: **[TEXT BOX]**

Scales:

1. Never
2. Occasionally but less than once a month
3. 1-3 times a month
4. 1-2 times a week
5. 3 or more times a week
6. I do not know

Base: all respondents

QII.2D. **[ACCORDION]**

<u>Since</u> the **March 2020 stay-at-home Executive Order from Governor Newsom**, how often has your household ordered take-out food or food online and had it delivered?

Statement:

a. **Eat on site** (at a restaurant, café, fast food, or food court)
b. **Take-out food** (e.g., drive-thru, click & collect, in-person pickup, or curbside pickup)
c. **Online food order with delivery** (via DoorDash, Grubhub, Postmates, UberEats, or similar)

Scales:

1. Never
2. Occasionally but less than once a month
3. 1-3 times a month
4. 1-2 times a week
5. 3 or more times a week
6. I do not know

Base: all respondents

DISP6 [DISP]

Finally, we would like to ask you a few questions about how your household will likely shop for groceries and prepared meals **<u>after</u>** the Covid-19 pandemic is over (when there are no more cases in the U.S.).

Base: all respondents

QII.1A [ACCORDION]

<u>After</u> the Covid-19 pandemic is over, how often do you think your household will use thefollowing grocery shopping options?

Statement:

a. **In-person grocery shopping** in a brick-and-mortar store or a farmers market
b. **Online purchase of groceries with home delivery** (e.g., via Amazon Fresh, Instacart, or Costco grocery)
c. **Online order of groceries with store pick-up** (via drive-thru, in-store pickup, or curbside pickup)
d. Other. Please briefly describe: **[TEXT BOX]**

Scales:

1. Never
2. Occasionally but less than once a month
3. 1-3 times a month
4. 1-2 times a week
5. 3 or more times a week
6. I do not know

Base: all respondents

QII.2A [ACCORDION]

<u>After</u> the Covid-19 pandemic is over, how often do you think your household will get take-out food or order food online and had it delivered?

Statement:

a. **Eat on site** (at a restaurant, café, fast food, or food court)
b. **Take-out food** (e.g., drive-thru, click & collect, in-person pickup, or curbside pickup)
c. **Online food order with delivery** (via DoorDash, Grubhub, Postmates, UberEats, or similar)

Scales:

1. Never
2. Occasionally but less than once a month
3. 1-3 times a month
4. 1-2 times a week
5. 3 or more times a week
6. I do not know

Base: QII.2A_c=2,3,4,5,6,refused

QII.3A [S]

<u>After</u> the Covid-19 pandemic is over, do you think your household would purchase a subscription plan for online food delivery?

For a monthly subscription fee of $**[INSERT SELECTED $]**, you would get unlimited free and fast deliveries (delivered directly to your home as soon as your order is ready) from participating restaurants within 15 miles of your house.

PROGRAMMER: Randomly select $ in {$5.99, $6.99, $7.99, $8.99, $9.99, $10.99, … $19.99}, i.e., $1.00 increments

1. Yes, we would purchase this free meal deliveries subscription plan
2. No, we would not purchase this free meal deliveries subscription plan

Base: QII.3A=1

QII.4A [ACCORDION]

With your monthly subscription fee of **$[INSERT SELECTED $]**, how much do you think your household will be spending on online food orders with delivery after the Covid-19 pandemic is over?

Restaurant meals purchases <u>after</u> the Covid-19 pandemic is over.
Monthly subscription fee: $[INSERT SELECTED $]

Statement:

a. Food order up to $20 (including taxes) + no delivery fee + tip
b. Food order of $21 to $60 (including taxes) + no delivery fee + tip
c. Food order of $61 to $120 (including taxes) + no delivery fee + tip
d. Food order over $120 (including taxes) + no delivery fee + tip

Scales:

1. Occasionally but less than once a month
2. 1-3 times a month
3. 1-2 times a week
4. 3 or more times a week
5. I do not know

Base: xretail=2

QII.6a [M]

We would like to understand how often you shop for groceries at different types of stores.

From which types of stores have you purchased groceries in the past 3 months?

1. Supermarket/Grocery store
2. Grocery website (such as Peapod, Amazon or AmazonFresh)
3. Discount store (such as Target, Walmart)
4. Farmer's market
5. Warehouse Club store (such as BJ's, Costco)

6. Dollar store (such as Dollar General, Dollar Tree)
8. None of these **[S]**

Base: xretail=2

QII.8 [M]
Do you or does any member of your household use the following rideshare companies?

1. Uber
2. Lyft
3. Sidecar
4. Gett
5. Curb
6. Via
7. Other
8. None of these **[S]**

Base: xretail=2

QII.7 [S]
Which of the following best describes your household's experience with subscription services for self-prepared meals (meal-kits) such as Blue Apron, HelloFresh or Home Chef?

1. Currently use a service like this
2. Used a service like this in the past, but do not currently
3. Never used a service like this, but considering it
4. Never used a service like this, and not interested
5. Not familiar with services like this

Base: xretail=2

QII.7a [M]
Do you or does any member of your household use the following grocery delivery companies?

1. Thrive Market
2. Google Express
3. Instacart
4. Shipt
5. Other
6. None of these **[S]**

Base: xretail=2

QII.9 [S]
Within the past 3 months, have you used a meal delivery service such as UberEats, DoorDash, GrubHub or similar services?

1 Yes

2 No

Base: xcu2=2
Randomize list

CU44 [ACCORDION]
How much do you agree with the following statements?

Statements in row:
1. Others rely on me for advice about technology
2. I often buy a new technology or, device, as soon as it goes on sale
3. I like surfing the internet for fun
4. I tend to watch less TV on a traditional television because I watch video online
5. I like to post online video content that I create (such as on YouTube)
6. I use social networking to communicate with others more than email and instant messenger
7. I am fine with advertising on mobile phones
8. I would pay to watch a TV show or movie to avoid commercials

9.I have had to delay some technology purchases because I didn't have the money

10. I like to buy electronics or technology from a physical retail store
11. I like to buy technology brands that are environmentally friendly
12. I always buy the lowest priced electronics or technology

Answers in column:
1. Do not agree
2. Somewhat agree
3. Agree
4. Strongly agree

Base: all respondents

QII.F1 [TEXT]
Thank you for participating in our survey. Please let us know if you have any comments orsuggestions: