Barriers to Reducing the Carbon Footprint of Transportation Part 1: Support to the Clean Miles Standard Policy Making

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16. Abstract
Transportation Network Companies (TNCs), also referred to as ridehailing companies, have experienced rapid growth in the past decade. This report focuses on the quickly evolving transportation patterns resulting from the adoption of ridehailing as part of the efforts accompanying the implementation of the Clean Miles Standard (CMS) regulation. Based on the analysis of survey data collected in four California metropolitan regions before the COVID-19 pandemic, this report summarizes the findings from three studies, focusing on (1) the use of ridehailing among traveler groups with different multimodal travel patterns, (2) the substitution of ridehailing for other modes, and travel induced by ridehailing, and (3) the use of pooled ridehailing services, in which multiple passengers share the same vehicle for all or a portion of their trips. The results from these analyses reveal that transit users are more likely to be ridehailing users. Individuals without a household vehicle and identifying with an underrepresented minority group are more likely to use ridehailing for essential (rather than for discretionary trip) purposes. Over 50% of the ridehailing trips replaced a transit, active, or carpooling trip, or created new vehicle miles. Lower-income individuals, people of color, females, and younger individuals are more likely to choose pooled ridehailing over the single-user ridehailing service. Trips that originate in high-density areas are also more likely to be pooled. Furthermore, being a frequent ridehailing user is associated with greater use of pooled ridehailing, whereas not having to pay for a trip (e.g., a work-related trip paid for by an employer) reduces the likelihood of pooling.

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Disclaimer

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The data used in this study were collected by the Sacramento Area Council of Governments (SACOG) with their regional household travel survey and by the San Diego Association of Governments (SANDAG), Southern California Association of Governments (SCAG), Metropolitan Transportation Commission (MTC), and San Francisco County Transportation Authority (SFCTA) as part of a project funded by a Sustainable Transportation Planning Grant from the California Department of Transportation (Caltrans).

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List of Acronyms

Acronym	Definition
BNEF	Bloomberg New Energy Finance
CARB	California Air Resources Board
CPUC	California Public Utilities Commission
EV	Electric Vehicle
GHG	Greenhouse Gas
ICE	Internal Combustion Engine
MTC	Metropolitan Transportation Commission
MPO	Metropolitan Planning Organization
NOx	Nitrogen Oxides
PM2.5	Particulate Matter 2.5
PT	Public Transit
SACOG	Sacramento Area Council of Governments
SANDAG	San Diego Association of Governments
SCAG	Southern California Association of Governments
SFCTA	San Francisco County Transportation Authority
TNC	Transportation Network Companies
VMT	Vehicle Miles Traveled
VOCs	Volatile Organic Compounds
ZEV	Zero Emission Vehicle

Executive Summary

Transportation Network Companies (TNCs) provide prearranged transportation services for compensation using an online-enabled application or platform that connects passengers with transportation providers, including drivers of personal vehicles, autonomous vehicles, charter-party carriers, and new modes of ridesharing technology that may arise through innovation and subsequent regulation. The services provided by TNCs are hereafter referred to as ridehailing.

In 2018, the TNC fleetwide average greenhouse gas (GHG) emissions per passenger mile traveled (PMT) in California was about 50% greater than the statewide passenger vehicle average (California Air Resources Board, 2019). In anticipation of the continued growth of ridehailing, the California legislature in 2018 enacted Senate Bill (SB) 1014, which mandated the development of the Clean Miles Standard and Incentive Program (CMS), a first-of-its-kind regulation that sets increasingly stringent targets for TNCs to transition their fleets to zero-emission vehicles (ZEVs) and reduce GHG emissions per PMT. The regulation was established by the California Air Resources Board (CARB) and is administered by the California Public Utilities Commission (CPUC). As part of the efforts to support the CMS, it is important to understand, through research, passenger behaviors, roots of GHG emissions produced by TNCs, and the potential ways to address the GHG impacts of TNCs. This project focuses on improving the understanding of the following aspects associated with the use of ridehailing:

1. The use of ridehailing among traveler groups with different multimodal travel patterns;
2. The substitution of ridehailing for other modes, and travel induced by ridehailing; and
3. The use of pooled ridehailing services, in which multiple passengers share the same vehicle for all or a portion of their trips.

The project was based on the analysis of survey data collected in four California metropolitan regions: the six-county Sacramento region, the nine-county Bay Area, San Diego County, and parts of Los Angeles and Orange counties. These data consisted of the 2018 Sacramento Regional Household Travel Survey, which sampled residents of the Sacramento Area Council of Governments (SACOG) planning area during the period from April 10th to May 21st, 2018, and the 2019 TNC Study, which sampled residents of the jurisdictions of planning organizations in the latter three regions: the Metropolitan Transportation Commission (MTC) and San Francisco County Transportation Authority (SFCTA), the San Diego Association of Governments (SANDAG), and the Southern California Association of Governments (SCAG), between November 2018 and November 2019.

The two data collections included a total of 508,128 non-ridehailing trips and 8,748 ridehailing trips, after data cleaning. The combined data from these two surveys are unique because 1) they consist of a large sample for exploring the inter-individual variations in travel decisions and their determinants, 2) each survey includes one consecutive week of observations per individual, which makes the data more reflective of intra-individual variation, 3) the trip information derived from the smartphone GPS tracking rMove app with the supplement of self-reported travel diary is believed to be more accurate than traditional self-reported information contained in other surveys, especially with regards to short-distance walking trips, and 4) they contain detailed trip information for each ridehailing trip including vehicle occupancy, trip cost, mode replacement and so forth. Three separate analyses were carried out to investigate each of the three main topics listed above, using different subsets of respondents and their trips. Therefore, each corresponding analysis uses a distinct subsample of the data.

The analyses presented in this project produced several key findings, including:

- A weighted latent class cluster analysis of commuters in the sample revealed four traveler groups with distinctive forms of modality who tend to adopt certain travel modes over the others: single-occupancy vehicle (SOV) drivers, carpoolers, transit users, and cyclists. Members of the transit user group are most likely to use ridehailing. For each traveler group, their most frequently used mode of travel would be often selected instead of ridehailing, if ridehailing services were not available. For example, car users would take car-based modes, while transit users would take transit. SOV drivers and carpoolers are more likely, than members of the other groups, to use premium TNC services (e.g., Uber Black), whereas transit users and cyclists are more likely to use pooled services (e.g., Uber Pool).
- Respondents to the 2019 TNC Study without a household vehicle or identifying with an underrepresented racial or ethnic minority group were least likely to cancel a trip if ridehailing services were unavailable, suggesting their more frequent use of ridehailing for essential rather than discretionary purposes. It was also found that the substitution of private car travel with ridehailing was predicted along racial, ethnic and income dimensions: racial and ethnic minority individuals and people from the lowest-income households in the sample were less likely than their White and higher-income counterparts to use their own car if ridehailing services were unavailable.
- Among the subsample used to analyze modal substitution and travel induced by ridehailing, over 50% of the ridehailing trips were found to replace a transit, active, or carpooling trip, or created new vehicle miles, with transit being the most substituted mode overall (30%). Not owning a household vehicle and using a pooled service were associated with the substitution of transit.
- With regards to the choice to use a pooled ridehailing service (e.g., UberX Share) over a traditional solo (i.e., single-user) ridehailing service (e.g., UberX), results show that lower-income individuals, people of color, females, and younger adults are more likely to choose pooled ridehailing. The research shows that trips that originate in high-density areas are also more likely to be pooled. In addition, there was an association between being a frequent ridehailing user and greater use of pooled ridehailing, whereas having company-sponsored trip payment would in turn reduce the likelihood of pooling for the same population.

Overall, the results of these research efforts provide evidence that the relationships between ridehailing and the use of other modes of transportation at the individual level are nuanced and depend on the individual's sociodemographic characteristics and travel patterns; however, the analysis of the data available for this project suggest that ridehailing, overall, tends to often replace the use of more sustainable modes of travel and/or generate new vehicle miles of travel. Furthermore, the research findings include racial, ethnic, and income considerations associated with the substitution patterns of ridehailing for other modes of travel and the use of pooled ridehailing, which motivate policies to address the transportation needs of underserved segments of the California population.

Among the study's limitations, it should be noted that the project is based on the analysis of data collected before the COVID-19 pandemic. Therefore, it refers to travel behavior choices and service conditions that were present in those years, which might not be entirely applicable to the modified post-pandemic conditions of the transportation sector. Additional research would be recommended to evaluate how these relationships might have evolved in recent years.

1 Introduction

Transportation Network Companies (TNCs) or ridehailing companies (e.g., Uber, Lyft) provide prearranged transportation services for compensation using an online-enabled application or platform that connects passengers with transportation providers, including drivers of personal vehicles, autonomous vehicles, charter-party carriers, and new modes of ridesharing technology that may arise through innovation and subsequent regulation. This type of service has experienced rapid growth in the past decade (Hou et al., 2020). For instance, Uber increased its global revenue from $0.4B to $14.1B in only five years (2014-2019) of which their passenger mobility segment generated about 76%, and 60% came from the U.S. and Canada regions (Iqbal, 2022).

Some studies have suggested that TNCs have positive impacts such as complementing public transit and active transportation by providing a first- or last-mile mode to travelers as part of multimodal trips (Conway et al., 2018; Feigon & Murphy, 2018; Hall et al., 2018; Sikder, 2019). TNCs may also have the effect of reducing car ownership (Henao & Marshall, 2018; Moody et al., 2021; Zou & Cirillo, 2021), for example, Bansal et al. (2020) found that around 10% of TNC users in the U.S. postponed the purchase of a new car due to the availability of ridehailing services, while Hampshire et al. (2017) learned that 45% of survey participants switched to the use of personal vehicles in response to Uber and Lyft's service suspension from Austin, Texas, and 8.9% of participants reported purchasing a new vehicle. Proponents of ridehailing claim this effect as beneficial to mitigate equity issues caused by car ownership such as the costly space devoted to parking. In California, more than two thirds of the cities require a minimum of two parking spaces per home in multi-family housing, which comes at a high cost for the residents (averaging $23,000 per space) whether they own a car or not, (Friedman & Shoup, 2021) with non-owners often being the least wealthy[1] (Bureau of Transportation Statistics, 2011).

On the other hand, there is evidence that ridehailing services cause multiple negative impacts. TNCs have been found to negatively impact the use of established and more sustainable transport options, such as public transit, walking, and biking, drawing people away from these more sustainable modes based on trip duration, convenience, and travel comfort. According to Schaller (2018), about 60% of ridehailing users in large metropolitan areas in the U.S. would have used public transit, walked, biked, or not made the trip at all if ridehailing had not been available. Public transit is often perceived by people to be a poor alternative to cars; attributes that go beyond the monetary aspect such as travel time, convenience, and mobility freedom (accessibility) contribute to the total experience of the trip and are often not satisfied by public transit (İmre & Çelebi, 2017; Moody et al., 2021; Sampo, 2021). Multiple studies draw the conclusion that TNCs drive down the ridership of public transit (Diao et al., 2021; Hall et al., 2018; Tang et al., 2019). A decline in transit ridership in favor of ridehailing can cause a negative cycle characterized by increased vehicle miles traveled (VMT) and decreased revenue for public

[1] U.S. households with an annual income of less than $25,000 are almost nine times less likely to own a vehicle than those with incomes greater than $25,000 (Bureau of Transportation Statistics, 2011).

transportation, which in the U.S. is largely funded by state and local governments who often already do not have the financial means to make investments to enhance this sector[2] (Mawad, 2021). Several authors suggest that ridehailing has increased VMT, road congestion and greenhouse gas (GHG) emissions (Erhardt et al., 2019; Henao & Marshall, 2018; Wu & MacKenzie, 2021). Ward et al. (2021) shows that switching from personal vehicles to ridehailing may increase social costs by 30–35% due to externalities such as congestion, collisions, damaged vehicles and infrastructure, and climate impacts, unless TNC vehicles are zero-emission and TNC rides are pooled. Ward et al. (2021) add that although substituting travel by one's car with ridehailing reduces local air pollution (NO_x, $PM_{2.5}$, VOCs) specifically in urban contexts—due to cleaner TNC vehicles and reduced "cold-start" emissions per passenger distance traveled—the increased travel caused by the "deadheading" phenomenon (i.e., miles between trips without any passenger on board) leads to about 20% more fuel consumption and greenhouse gas emissions compared to trips made with private vehicles. If the share of global miles traveled by passenger vehicle attributable to ridehailing trips continues to follow the trend projected by the Bloomberg New Energy Finance (NEF), i.e., from less than 5% in 2019 to 19% by 2040 (Bloomberg NEF, 2019), then regulations must be formed to ensure the growth of ridehailing services is sustainable (California Air Resources Board, 2019).

It is from this perspective that the California legislature enacted Senate Bill (SB) 1014, which mandated the development of the Clean Miles Standard and Incentive Program (CMS)[3], a first-of-its-kind regulation that sets increasingly stringent targets for TNCs to transition to zero-emission vehicles (ZEVs) and reduce GHG emissions per passenger mile traveled. The California Air Resources Board (CARB) is in charge of defining the standard, while the California Public Utilities Commission (CPUC) is responsible for its implementation, for which the rulemaking process began in 2023.

The 3 Revolutions Future Mobility (3RFM) team supports the CMS by investigating the impacts of ridehailing on people's travel behavior using survey data from four regions of California under the jurisdiction of the following metropolitan planning organizations (MPOs): 1) Sacramento Area Council of Governments (SACOG) for the six-county Sacramento region, 2) the Metropolitan Transportation Commission (MTC) and the San Francisco County Transportation Authority (SFCTA) for the nine-county Bay Area, 3) the San Diego Association of Governments (SANDAG) for San Diego County, and 3) the Southern California Association of Governments (SCAG) for the counties of Los Angeles and Orange. The data were collected over a 7-day period via the *rMove* app, which passively collected spatial information on participants' trips by ridehailing and other modes using GPS, and actively asked them survey questions pertaining to their trips, general travel behavior, land use, and personal characteristics at the end of each trip and day. Based on this rich dataset, the project team investigated the behavioral roots of GHG

[2] Examples of investments include expanding the public transit network, reducing fares for transit-dependent individuals, increasing the supply of shared mobility to fill first- and last-mile gaps, improving biking infrastructure, limiting car-centric sprawl, and many others.
[3] https://ww2.arb.ca.gov/our-work/programs/clean-miles-standard

emissions produced by ridehailing and the potential ways to ameliorate the impacts of TNCs, focusing on the following areas that the researchers discuss in detail in three distinct sections of this report: 1) the use of ridehailing by traveler groups with different multimodal travel patterns; 2) the substitution of ridehailing for other modes, and travel induced by ridehailing; and 3) the use of pooled ridehailing services, in which multiple passengers share the same vehicle for all or a portion of their separate trips. The research team investigated the following research questions:

Table 1 Overview of the research questions investigated in this report

Research questions	Chapter
How are distinctive traveler groups characterized by their trip profiles (i.e., weekly trip frequency by modes) and personal characteristics?	4
What is the association between multimodality and the adoption/usage of ridehailing by traveler groups?	5
What are the personal and trip characteristics associated with ridehailing users' decisions to substitute other modes of travel or conduct entirely new trips with ridehailing?	6
What are the factors, including non-monetary or travel utility (and disutility) factors, that affect the choice to use pooled ridehailing, and to what extent do they affect people's choices?	7

The remainder of this report is organized into 7 sections. Section 2 includes a review of the ride-haling research literature relevant to this report's focus areas, i.e., the modal substitution and induced travel effects of ridehailing, the role of ridehailing in the context of multimodality, and the existing work on the factors that influence the choice to use pooled ridehailing services. Section 3 describes the dataset used in this report. Section 4 presents the results of a general exploratory analysis of the dataset. Sections 5, 6, and 7 describe analyses specific to the three main focuses presented in this report: a latent-class cluster analysis on ridehailing use, travel patterns and multimodal lifestyle; a multinomial logit model of modal substitution and induced travel of ridehailing; and a mixed logit model of the use of pooled ridehailing services. Section 8 presents the conclusions of the study.

2 Literature Review

There is a growing body of literature investigating the impacts of ridehailing services. This literature review is organized into three sections that each cover a major topic in ridehailing research: section 2.1 examines the modal substitution and induced travel effects of ridehailing, section 2.2 reviews the role of ridehailing in the context of multimodality, and section 2.3 explores the existing work on the factors that influence the choice of pooled ridehailing services.

2.1 Modal Substitution and Induced Travel

Multiple studies have investigated the alternative travel options that riders would choose if ridehailing services were not available. In doing so, such studies have revealed the rate of substitution of ridehailing for other transport modes, and the occurrence of induced travel (i.e., trips that would not have occurred without ridehailing services). Induced travel of ridehailing implies an increase in VMT and associated contributions to congestion, energy use, and greenhouse gas emissions. On the other hand, induced travel can also mean (and, to some extent, is the result of) enhanced mobility and ensuing opportunities for communities with poor access to other modes (Tirachini, 2020). Modal substitution may also be beneficial if, for example, pooled ridehailing trips replace single-occupancy private car trips (Shaheen & Cohen, 2019)—assuming that the additional deadheading to pick up and drop off passengers does not lead to an increase in VMT with the pooled ridehailing option—but is more often found to be detrimental as ridehailing drains passengers from more sustainable modes such as public transit (Barajas & Brown, 2021; Young et al., 2020). This section summarizes previous studies on the rates of modal substitution and induced travel of ridehailing.

In his international review of studies about the effects of ridehailing on sustainability and travel behavior, Tirachini (2020) found that the three modes most often replaced by ridehailing are taxis, public transit, and private cars, respectively. Multiple international studies have reported induced travel rates for ridehailing between 5 and 7% (Alemi et al., 2018; Gehrke et al., 2019; Lavieri & Bhat, 2019a; Rayle et al., 2016; Tirachini & Gomez-Lobo, 2020), while other studies have reported rates as high as 12.2% (Henao & Marshall, 2018) and as low as 0.4% (Tang et al., 2019). Two studies based in the United States directly compared the modal substitution patterns of car owners and non-owners (Mahmoudifard et al., 2017; Rayle et al., 2016). Both studies—one based in San Francisco, the other in Chicago—found that car owners were more likely to have replaced a private car or taxi trip with ridehailing than non-owners, who in turn were more likely to have replaced a public transit trip. Alemi et al. (2018) analyzed the responses to a 2015 survey of Millennials (aged 18–34 years old) and members of Generation X (aged 35–50 years old) in six regions of California to understand the factors affecting ridehailing use among those groups. Most people in both age categories reported that they would have taken a taxi if ridehailing services had not been available for their last trip made with Uber or Lyft. Millennials were more likely to have replaced public transit and active travel than members of Generation X, who in turn would have been more likely to receive a ride from someone else were ridehailing not available. Alemi et al. (2018) found also that Millennials have a slightly higher rate of induced travel at 9.2% compared to Generation Xers at 7%.

Results from two survey studies indicate that ridehailing likely increases VMT in major cities. Among ridehailing users, in a 2016 survey of residents in seven metropolitan areas in the United States, Clewlow and Mishra (2017) estimated that between 49 and 61% would make fewer trips or would have traveled by walking, biking, or public transit where ridehailing services not available. Notably, a plurality (22%) of respondents reported that they would make fewer trips, which once again alludes to the presence of induced demand. In the Greater Boston Region, most respondents (59%) in an intercept survey of ridehailing passengers would have used public transit, active modes or would not have made their present trip where ridehailing service not available (Gehrke et al., 2019).

A few studies in different parts of the world have investigated the factors that affect modal substitution and induced travel of ridehailing. In a survey study of commuters in the Dallas-Fort Worth Metropolitan Area, Lavieri and Bhat (2019a) found people aged 18–64 were more likely to substitute ridehailing for active travel and transit than people aged 65 or older. A common pattern of lower household income being associated with a higher probability of substituting ridehailing for transit trips was found in Chicago (Mahmoudifard et al., 2017), Boston (Gehrke et al., 2019), and a study covering ten cities across China by Tang et al. (2019). Based on this finding, some have recommended policies to reduce the costs of ridehailing for lower-income people who may depend on the services for mobility (Gehrke et al., 2019). Mahmoudifard et al. (2017) found the number of bus stops at a trip's origin and destination to be positively associated with the choice of a bus ride if ridehailing services were not available in Chicago. Similarly, people in Boston who live near a rapid transit station were more likely to choose an active or transit mode than a vehicle-based mode if ridehailing services were not available (Gehrke et al., 2019). These findings suggest that introducing ridehailing to a transit-accessible area may attract people away from more sustainable travel options. On the other hand, the lack of public transit services is shown to be a strong motivation for people to use ridehailing services rather than walking or biking in China (Tang et al., 2019). Furthermore, there is evidence that ridehailing affects the use of bus and rail differently. In major Chinese cities, Tang et al. (2019) claim that the supply of bus routes cannot meet demand, which leads some travelers to opt for ridehailing services instead. In contrast, they found that trips on longer metro routes were less likely to be replaced by ridehailing.

In terms of the substitution of ridehailing for private car and taxi travel, there are conflicting results on the effects of the trip duration and parking issues. Gehrke et al. (2019) found that longer trips, which they identified by proxy through a higher ridehailing fare, predict the replacement of vehicle-based trips in Boston. On the contrary, shorter trips predicted the replacement of taxi trips in studies in Lebanon (Tarabay & Abou-Zeid, 2020) and China (Tang et al., 2019). Furthermore, whereas Tang et al. (2019) found parking issues to be a major factor in the replacement of private car trips, Tarabay & Abou-Zeid (2020) claimed that drivers in their study were not very sensitive to increases in the cost or search time for parking. However, the latter authors concluded that more expensive and difficult parking may make people more sensitive to reductions in ridehailing fares.

There have been few studies of the factors that affect induced travel of ridehailing. Gehrke et al. (2019) found that transit pass possession, the use of a pooled ridehailing service, and high per capita employment at one's home location predict induced ridehailing trips in Boston. Transit pass holders likely rely on transit and would have limited access to destinations outside the transit network if ridehailing services were not available. The lower cost of pooled rides may have enabled some trips. Lavieri and Bhat (2019a) found that urban and suburban residence, as opposed to rural, and high household vehicle availability predicted induced travel of ridehailing in the Dallas-Fort Worth Metropolitan Area. Furthermore, induced trips were more likely to be single occupancy.

As highlighted by Tirachini (2020), most ridehailing users do not replace other modes of travel entirely but change their intensity of use of other modes. People's patterns of use of multiple modes over a period are studied under the term multimodality. The next section begins with an overview of multimodality studies in general, then focuses on the travel patterns of ridehailing users in particular.

2.2 Multimodality

"*Modality*" refers to an individual's latent tendencies to use (or not) certain means of travel on a regular basis, which are often measured via their frequencies of using a wide set of travel modes over a period. Modality is a representation of the repetitive nature of travel behavior, which is influenced by higher-level orientations or lifestyles (Vij et al., 2013). A series of terms and definitions have been used in the literature to describe different modality styles. Many terms have been used to describe travel patterns oriented around the private car (Urry, 2004). For instance, "Car-free" describes zero-car households that are liberated from the costs and hassles of car ownership, while "car-less" represents zero-car households which continue to have mobility burdens (Brown, 2017). In terms of the intensity of car use, "car-dependent" indicates a lifestyle relying mainly on cars, while "car-light" represents the opposite. In attempts to shift away from automobiles, cities promote "multimodality," which refers to more flexible use of different transport options, "intermodality," which refers to the use of multiple modes within one trip or a chain of trips, and "multioptionality," which is conceptualized as creating the necessary preconditions for multimodal behavior (Groth, 2019). The growth of ridehailing services in cities is controversial in part due to questions surrounding whether they promote or discourage multimodality.

It is necessary to investigate a person's day-to-day behaviors to capture the typical stability or variability of their modality. Some studies rely on consecutive observations over multiple weeks or multiple observations at several points in time i.e., longitudinal observations, which can offer better quality data to explore the rhythm and long-run dynamics of travel behavior. However, such studies tend to be constrained by the prohibitive cost of survey administration and low retention rates, which leads to smaller sample sizes and potential biases. Examples include the research project Mobi*drive* with a six-week continuous travel diary survey in two German cities (Axhausen et al., 2002), the Netherlands Mobility Panel study with a three-day travel diary conducted repeatedly with the same participants over five years (Hoogendoorn-Lanser et al., 2015), and the Puget Sound Transportation Panel Survey (Puget Sound Regional Council, 2002). To reach a middle ground, some studies have suggested that consecutive observations over one week tend to be sufficient (Buehler & Hamre, 2015; Kuhnimhof et al., 2006; Nobis, 2007). For instance, Pas used the weekly travel-activity pattern to describe respondents' travel-related lifestyles (Pas, 1988) and Nobis defined the "multimodality" in his study as the use of at least two distinct travel modes within a week (Nobis, 2007). In terms of the methods to study multimodality, researchers have used deterministic clustering techniques (Buehler & Hamre, 2015) or probabilistic latent class analyses (Vermunt & Magidson, 2002) to identify distinctive traveler groups based on their mode use patterns.

Previous studies tend to identify different travel groups that differ in their attitudes towards auto use, socio-demographics, use of different travel modes and associated built environment. However, those studies are mainly focused on traditional modes with "walking" often being omitted or heavily underreported, which is a common issue of the traditional travel diary (Handy et al., 2002). Moreover, newer travel modes such as ridehailing have largely not yet been incorporated into multimodality analyses due to their novelty. Some existing studies have suggested that multimodalists are most likely to use ridehailing. For instance, Alemi and Circella estimated a latent-class model with a continuous distal outcome to classify individuals based on their travel patterns and to investigate their variation in vehicle miles driven (Alemi & Circella, 2019). Among three latent classes that were identified, multimodal drivers who use a variety of transportation modes (although driving is still their primary mode) have the highest average frequency of ridehailing usage. Unsurprisingly, the latent class of "multimodal no car users" also has a high frequency of ridehailing use, while the latent class of "drivers" has the lowest. On the contrary, studies also suggested that ridehailing reduces the multimodality of ridehailing users. Chen et al. explored the impact of pooled ridehailing on multimodal urban mobility, especially on public transit, based on real-world ridehailing trip requests data and a user behavior survey (Chen et al., 2021). The type of pooled ridehailing the authors considered is called ridesplitting, which Shaheen et al. defined as when "riders with similar origins and destinations are matched to the same driver and vehicle in real time, and the ride and costs are split among users" (Shaheen et al., 2016). Chen et al. found that ridesplitting reduces the usage of taxis and private cars, but simultaneously attracts passengers from non-passenger/private vehicles (e.g., bus and metro transit). These mixed findings emphasize the need to examine this topic further. Accordingly, one of the studies presented in this report attempts to disentangle the relationship among ridehailing use, travel patterns and multimodality, with a latent class analysis.

2.3 Factors Affecting the Use of Pooled Ridehailing

Pooled (or shared) ridehailing can enable riders with roughly the same origin and destination to share a ride in a TNC vehicle. Many point to the potential of pooled ridehailing to cut unnecessary VMT by increasing passenger miles traveled (PMT) through higher occupancy and matching of passengers (Shaheen, 2018). If this service does not lead to the replacement of public transit and active modes, or remarkable additional mileage caused by deadheading, the higher vehicle occupancy typical of pooling could contribute to reducing the negative environmental and societal impacts of single-passenger travel, i.e., a personal car driven alone or a single-passenger ridehailing trip.

This section of the literature review considers studies that examine the barriers and motivations to adopt pooled ridehailing services. (Alonso-González et al., 2020) analyzed user preferences towards pooled on-demand services in the Netherlands and found the value of in-vehicle time to be higher than the time spent waiting for the vehicle (especially for working individuals), and the value of total travel time to be higher for commuting than for leisure trips. Another study (Shaheen et al., 2021) investigated the factors influencing individuals' choice to pool or ride alone in four metropolitan regions in California. The authors found that sensitivity to waiting and walking time depends on the characteristics of the region, and that in-vehicle value of time changes across income groups. Home-based trips are less likely to be pooled, in comparison to commuting. Shaheen et al. (2021) also learned that females, unemployed or retired individuals, and low-income people are the most likely to pool, and those who tend to drive frequently are less likely to pool as compared to those who tend to frequently use more sustainable modes (e.g., transit, bikes).

Using data collected from a survey in the Dallas-Fort Worth Metropolitan Area, U.S., other researchers (Lavieri & Bhat, 2019a) investigated what influences the adoption of ridehailing, whether pooled or not. They found that living in low-density residential areas was a disincentive to the adoption of pooled ridehailing. The fact that both ridehailing and transit are more popular in dense areas is, on one side, positive because it disfavors driving, yet it indicates that ridehailing is competing with transit and active modes. Lavieri and Bhat (2019a) also found that privacy concerns, especially for white individuals, were a disincentive to the adoption of pooled ridehailing. Another study from Lavieri and Bhat (2019b) investigated the current choice and future intention, in a hypothetical driverless scenario, of people to take pooled or non-pooled rides in the Dallas-Fort Worth Metropolitan Area. Results from their research show that, especially for leisure trips, the presence of strangers in the vehicle reduces the likelihood of choosing to pool a ride. The authors also found that pooled ridehailing when escorting family or friends might be perceived as challenging. Furthermore, the added travel time typical of pooled ridehailing seems to be an even more significant barrier than the willingness to share a ride with strangers.

Another research from Kang et al. (2021) modeled the factors that influenced the likelihood of residents in Austin, Texas to use pooled vs. non-pooled ridehailing. The authors found that those who have a higher propensity for sharing and green lifestyles, that are employed and highly educated, were more likely to use pooled ridehailing. Furthermore, they found that tech-savvy people, females, older and white individuals are less likely to pool, and that living in a densely populated area leads people to choose pooled ridehailing. (Brown, 2019) used Lyft trips data in Los Angeles, California to analyze their correlation with the built environment and neighborhood socioeconomic attributes. The author found that most shared trips are made in high-density neighborhoods and by users living in low-income neighborhoods. Hou et al. (2020)

used Chicago-based TNC data to investigate the willingness to pool. They found that the willingness to pool increases as the duration, distance, or fare of the trip increases. It was observed that airport trips (especially drop-offs), trips starting or ending in zones with high income, or with high population and job density, as well as trips happening during the weekend have a lower willingness to pool. Using data collected through the DiDi ridehailing platform in Hangzhou, China, Ze et al. (2019) investigated youth behavior surrounding ridesplitting and found that most users are female, married, and educated. Travel cost, e.g., for avoiding parking issues and avoiding drunk driving, was also found to be positively associated with ridesplitting. Ridesplitting users were found to mainly shift from bus and taxi use, thus causing the decline in market share of buses and taxis. Another study from Sarriera et al. (2017) studied the decision to use pooled rides in the U.S. and learned that time and cost are important determinants in the selection of this mode, and to a lesser degree, the concern of a negative interaction during the shared trip. The authors found that females prefer to be matched with other females to reduce safety concerns. They also observed that the comfort and speed seem to be a competitive motivator to select pool ridehailing in comparison to active modes or public transit.

3 Surveys and Data

3.1 2019 TNC Study and 2018 Sacramento Regional Household Travel Survey

This section describes the dataset used to investigate the impacts of ridehailing services in California, which is composed of travel survey samples and sociodemographic and built environment variables from external data sources. The 2018 Sacramento Regional Household Travel Survey was administered in the six-county SACOG planning area during the period from April 10th to May 21st, 2018. The 2019 California TNC User Survey was administered between November 2018 and November 2019 as a consolidated study among the MTC, SFCTA, SANDAG, and SCAG MPOs. There are similarities and differences between these two surveys in terms of sampling strategy, data collection method, questionnaire contents and data weighting strategy, which makes it possible to fuse them together into one dataset, but also required the 3RFM research team to identify potential inconsistencies across regions. Table 2 describes the 2019 TNC Study and 2018 SACOG Household Travel Survey samples. For both surveys, the sampling and data collection was coordinated by the Resource Systems Group (RSG).

Table 2 2019 TNC Study and 2018 SACOG Household Travel Survey sample description

Dataset	2019 TNC Study			2018 SACOG Household Travel Survey
Geography	MTC/SFCTA	SANDAG	SCAG	SACOG
Non ridehailing trips	169,753	101,543	54,904	181,928
Non ridehailing survey participants	4,892	2,772	1,575	7,230
Ridehailing trips	5,151	1,578	1,102	917
Ridehailing survey participants	1,573	599	351	386

3.2 Sampling Strategy

While the SACOG survey seems to achieve a high level of representativeness of the population in the region, the California TNC survey focuses on individual adults aged 18 and over and is skewed towards TNC users and smartphone users. Both surveys use address-based sampling (ABS) and stratify their samples using the most recent American Community Survey (ACS) data at Census Block Group level at the time. This combined sampling approach increases the representativeness of the sample for the population being studied while also allowing for oversampling of specific types of respondents based on research interests. Both surveys have oversampled areas with a higher expected share of TNC users. The Bay Area survey also included a substantial oversample in San Francisco County, while the SCAG survey oversampled in transit-oriented areas. Besides ABS sampling, the SANDAG survey included an email-based sampling component. Furthermore, the SACOG survey also oversampled rural and low-income residents, as well as public and active transportation users, in addition to TNC users.

3.3 Data Collection Method

While survey invitations and recruitment letters were mailed to potential participants, both studies collected their data entirely online using a smartphone app-based data collection method. The main difference of their data collection process is that the California TNC survey conducted all their surveys through rMove ™ (an iOS or Android smartphone-based GPS tracking app) [4], while the SACOG survey also offered an additional option to complete the survey through rSurvey (an online survey instrument that does not require rMove). As a result, the California TNC survey excluded participation from non-smartphone-owning populations, which might be systematically different from the general population. On the other hand, using rMove to record travel data has several advantages. The rMove App can passively track movement trajectory, resulting in more accurate trip rates, travel times, distances and person-miles traveled. It also allows for the capture of "unlinked trips", which are multimodal trips that share a destination (e.g., "walk—transit—walk" commute to work). This is particularly useful for identifying access/egress modes for transit trips and providing a more accurate representation of regional travel behavior, including mode shares and trip distance.

3.4 Questionnaire Content and Variables

Both surveys collected extensive data on demographic characteristics and travel behavior data in two stages. The first stage was the "sign-up survey" or "recruit survey", which gathered information about household composition, socio-economic and demographic characteristics, vehicle ownership, and typical travel behavior. The second stage was the "travel diary", which began the day after respondents completed the sign-up survey and lasted for one week. The rMove App allowed for continuous recording of participants' physical trips throughout the day, while follow-up surveys collected detailed information on each trip, such as its purpose, mode of travel, park locations for those who drove and other relevant details. In particular, the surveys included comprehensive questions regarding ridehailing trips, including the type of services used (e.g., UberPool, Lyft Lux), whether participants shared their ride with others, who paid for the trip, and how they would have made the trip if ridehailing services were not available. If respondents completed the sign-up survey and provided complete travel diary information on at least one concurrent day during their travel period, they were treated as one "completed" data point. While there are some unique variables in each survey, there is a list of variables that both surveys share with consistent wording. For the purposes of this study, only these shared variables were used to ensure internal validity.

3.5 Weighting

To compensate for unequal selection probabilities and non-response biases, both surveys created weights that were used to adjust the sample to the population of interest. The SACOG Survey used *household-level* weights while the California TNC Survey used *individual-level* weights. All statistics presented in this paper, including population values, such as means,

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[4] https://rmove.rsginc.com/.

proportions, and ratios, were calculated using these weights. It should be noted that instead of directly using the expansion weights (which scale the sample up to the population) they were converted into proportional weights (which have a mean of approximately 1). This conversion is a common practice in statistical software, such as Mplus, when estimating models. By doing so, the effects of extreme weights are mitigated, and the sample still accurately represents the population of interest.

The combined data from these two surveys is unique for the following reasons: 1) It includes observations from four regions (two in Northern California and two in Southern California), which are the most populated areas in California, where most ridehailing drivers and riders are located. This presents a great opportunity to compare findings related to the ridehailing services across the state with greater socio-economic and geographic diversities. 2) It consists of a larger sample for exploring the inter-individual variations of modal decisions and their determinants. 3) It includes one consecutive week of observations per individual which makes it more reflective of individual variations. 4) The trip information derived from the smartphone GPS tracking App with the supplement of self-reported travel diary is believed to be more accurate than traditional surveys, especially with regards to short-distance walking trips (Bohte & Maat, 2009; Lee, Chen, Circella, & Mokhtarian, 2022; Tsui & Shalaby, 2006; Wolf, Oliveira, & Thompson, 2003). 5) It contains some unique trip information for each ridehailing trip including trip occupancy, trip cost, mode replacement and so forth.

3.6 External Datasets

To further enrich the dataset, the research team brought in several socio-demographic and built environment variables that were aggregated at the census block group level where survey respondents reside. The population density, job density, and median income of each block group were derived from 2019 American Community Survey (ACS) and LEHD Origin-Destination Employment Statistics (LODES) datasets. Moreover, the ‘walkscore’ of each block group was derived from walkscore.com. Neighborhoods with a higher walkscore are more walkable, with better access to public transit, and closer proximity to people and places.

4 Exploratory Data Analysis

4.1 TNC Users in California

Unless indicated, the findings presented in this section are based on the weighted data described in Figure 1. In addition, given that some variables were not available in the 2018 SACOG Regional Household Travel Survey, this region was at times omitted from parts of the further analyses (these occasions are indicated when relevant).

According to Figure 1, ridehailing services account for approximately 1% of all passenger trips in the MTC/SFCTA and SCAG regions, and 0.2% and 0.4% in the SACOG and SANDAG regions in California.

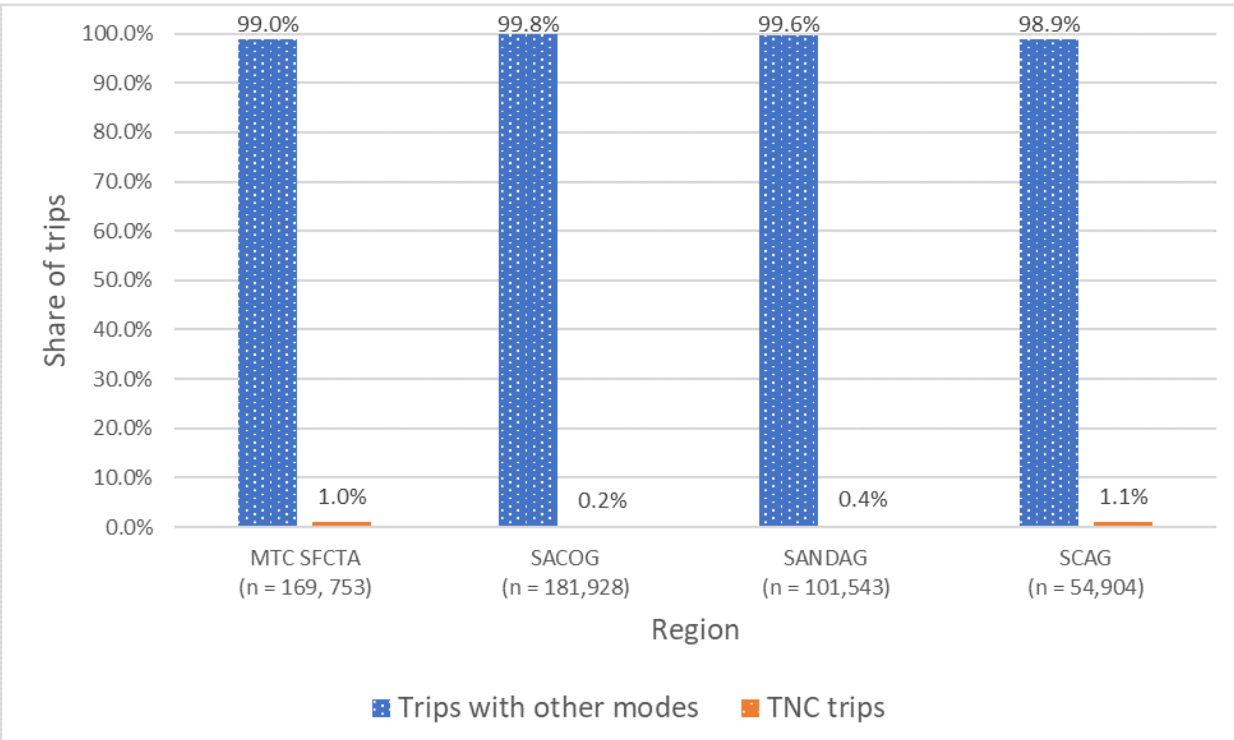

Figure 1 Total trips in sample (n= 508,128)

Figure 2 shows that about 50% of the trips in the sample are made by frequent users (i.e., those that use ridehailing 4 or more times per month). Of the reminder, half of the trips in the sample are made by occasional users (i.e., using ridehailing 1-3 times per month), and half by low-frequency users (i.e., less than once a month). In addition, Table 3 reports the distribution of socio-demographics of the ridehailing users.

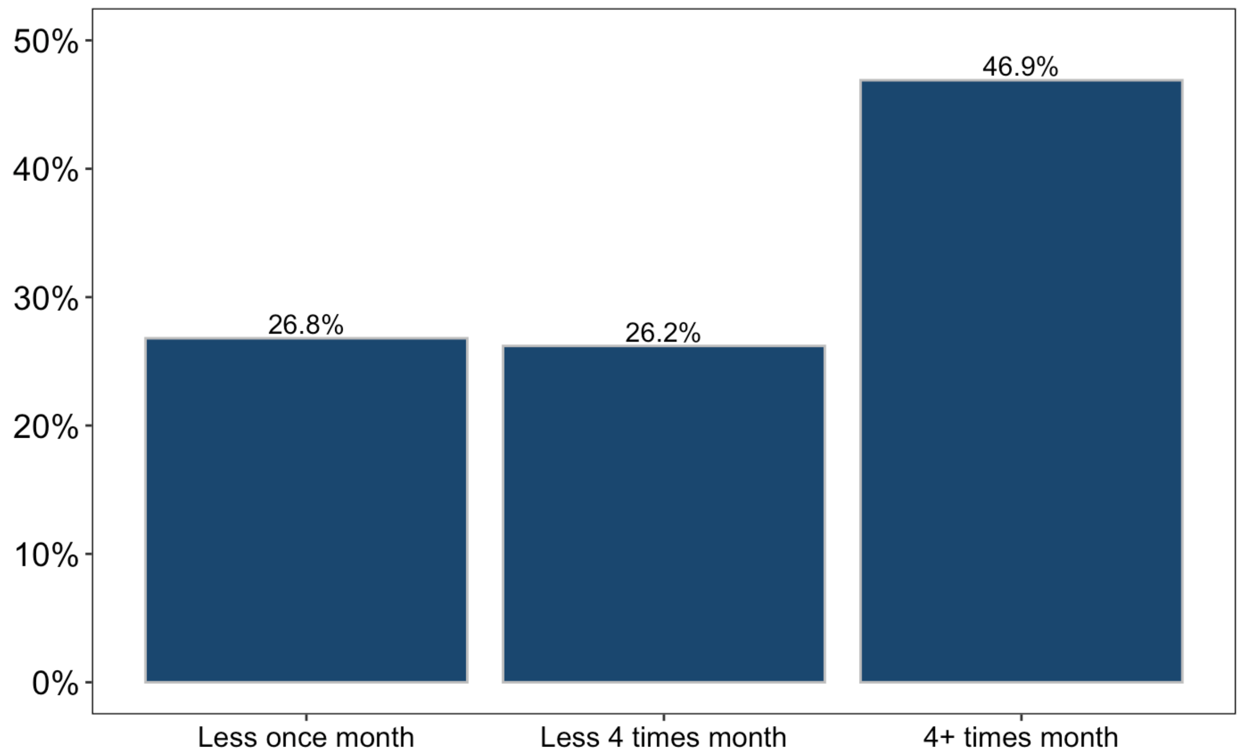

Figure 2 Ridehailing trips by travelers' frequency of use of the service (n=8,748)

Table 3 Sociodemographic characteristics of ridehailing users (n=2,909)

Variable	Level	Ridehailing trips frequency by the socio-demographic of the riders 4+ times month	Less 4 times month	Less once month
Gender	Female	55.4%	47.3%	48.7%
	Male	44.6%	52.7%	51.3%
		100%	100%	100%
Age	18-34	56.1%	50.7%	63.4%
	35-54	30.9%	40.6%	23.8%
	55-64	5.4%	3.0%	10.7%
	65+	7.7%	5.7%	2.1%
		100%	100%	100%
Race	Non-White	53.1%	54.6%	57.4%
	White	46.9%	45.4%	42.6%
		100%	100%	100%
Ethnicity	Non-Hispanic	72.1%	61.9%	59.8%
	Hispanic	27.9%	38.1%	40.2%
		100%	100%	100%
Student	Non-Student	76.2%	86.8%	82.3%
	Student	23.8%	13.2%	17.7%
		100%	100%	100%
Income	High	44.2%	61.3%	38.4%
	Low	35.7%	21.8%	46.4%
	Middle	20.1%	16.8%	15.2%
		100%	100%	100%

Figure 3 shows that frequent ridehailing users have a much lower household vehicle ownership rate than occasional (less than four times per month) and non-users (less than once a month). This may be partially explained by their predisposition to live in dense urban areas with a higher supply of driving alternatives.

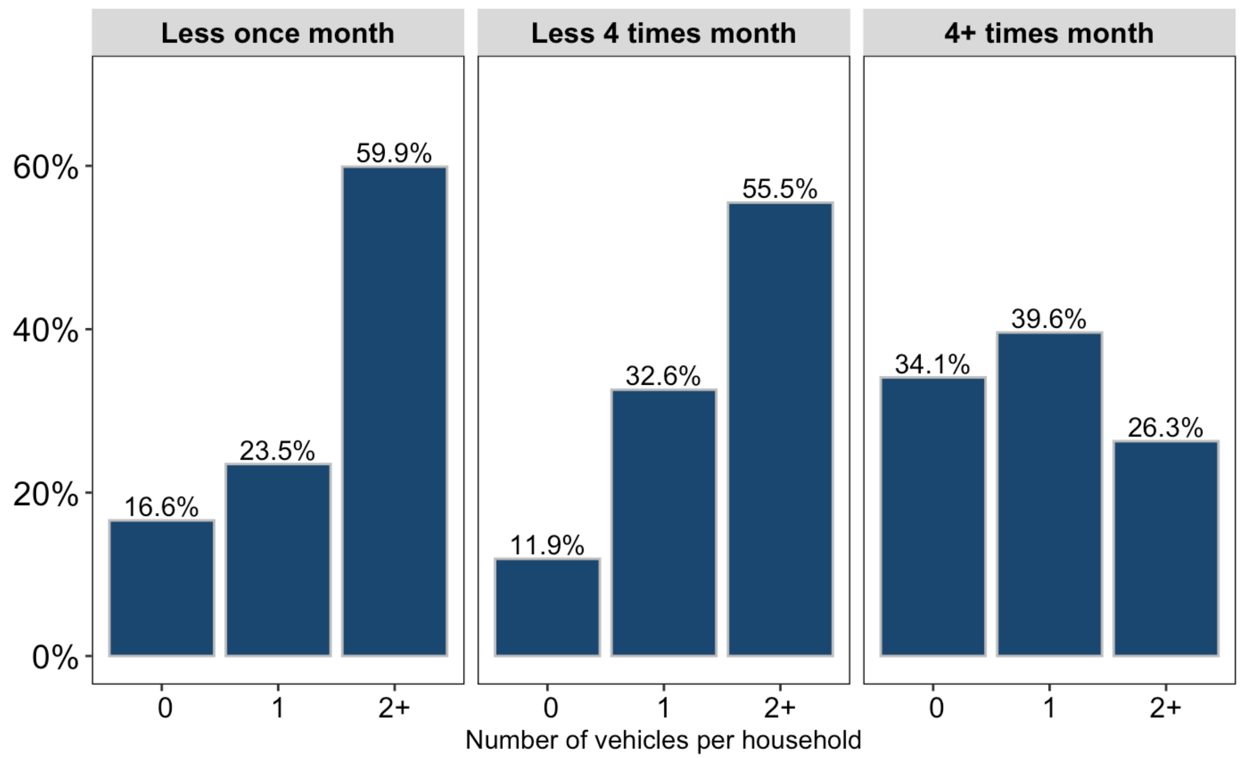

Figure 3 Household vehicle ownership across ridehailing users based on their ridehailing use frequency (n=2,909)

Regarding the destination purpose of the TNC trips collected in the sample (Figure 4), the data shows that leisure trips account for the largest share of ridehailing trips (33.4%), only 5.2% of ridehailing trips are undertaken for *mode transfer* purposes.

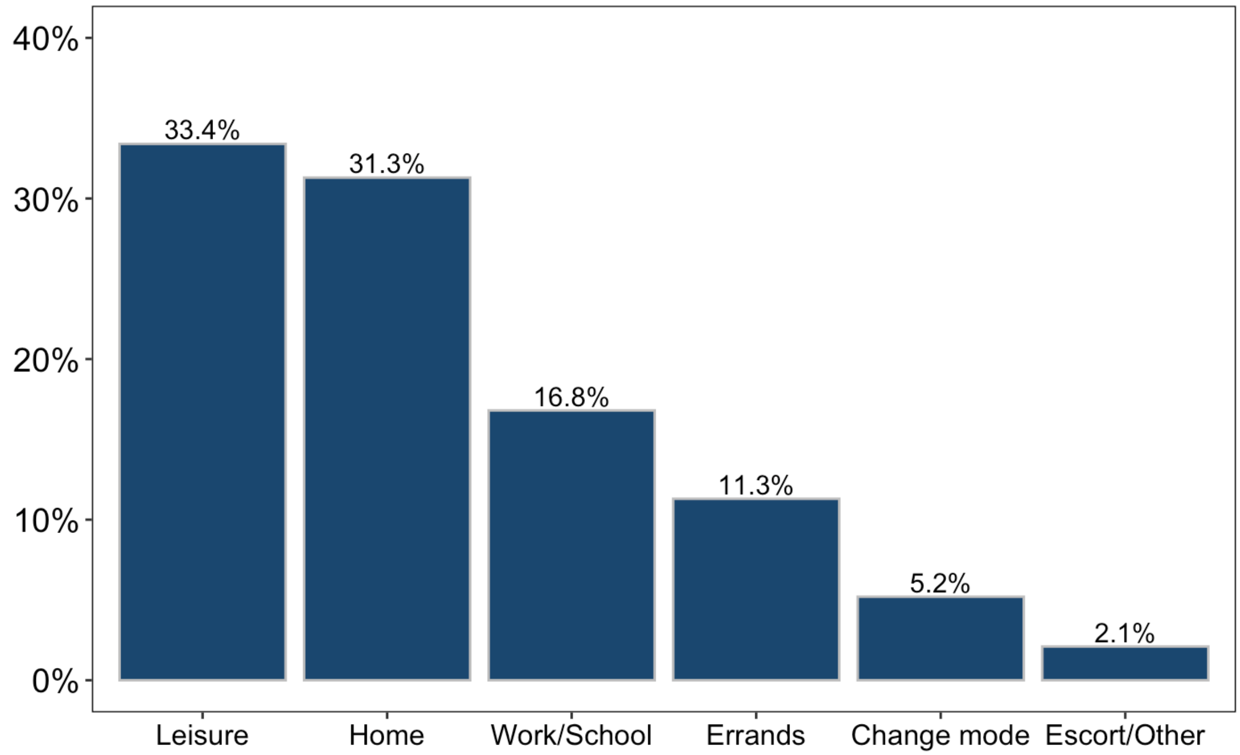

Figure 4 Ridehailing trips by trip purpose (n=8,748)

4.2 Secondary Data used to Gather Information on TNC Users in California

This section explores certain characteristics of the TNC users in California that were not available in the main dataset (3.1), via two other sets of survey-based data collections. The reported findings are based on unweighted data collected with the California Panel Survey and the United States "8-cities" Mobility Study by the project team of UC Davis[5]. Table 4 describes the datasets.

[5] https://3rev.ucdavis.edu/3rfm-research-program

Table 4 Descriptions of secondary datasets used to gather information on ridehailing users in California

Dataset	Year of Survey	Number of Observations	Geography
California Panel Survey	2018	3,740	California State
US ‘8-cities’ Mobility Study	2019–2020	1,334	San Francisco, Sacramento, Los Angeles

According to the California Panel Survey and the U.S. “8 cities” Mobility Survey, the ridehailing market penetration (observation of the installation of Uber or Lyft app) between 2018 and the end of 2019 - February of 2020 (before the beginning of the COVID-19 pandemic), shows that the proportion of respondents that have installed ridehailing applications on their phones increased by approximately 10 percentage points between 2018 and 2019-2020. Among respondents who have a ridehailing app installed on their phones, approximately a third of respondents use ridehailing services more than once a month. According to the data collected with the California Panel Survey and the US “8 cities” Mobility Survey, respondents use ridehailing primarily *to avoid paying or searching for parking*, and *to save time*. Other notable reasons for using ridehailing are *to avoid impaired driving*, due to safety concerns, and because *transit is either inconvenient or unavailable*. Shared or pooled (e.g., UberPOOL) ridehailing services are also used to save money. Ridehailing trips conducted during the weekday (Monday-Thursday, 5am-7pm) are more likely to be made to save time (56% of these trips). The proportion of high-income users that select “to save time” as a reason for using ridehailing is no different than the proportion of high-income ridehailing users (about 40% of the sample). Respondent who select “to feel safe” as a reason for using ridehailing are more likely to be females (58% of these respondents) and to travel at night (about 60% of these respondents).

5 Ridehailing Use, Travel Patterns and Multimodality: A Latent-class Cluster Analysis of One-week GPS-based Travel Diaries in California

5.1 Abstract

Based on the analysis of one-week GPS-based travel diary data from the four largest metropolitan areas in California, this study estimates a latent-class cluster analysis and identifies four distinctive traveler groups with different levels of multimodality. These groups are characterized by their distinctive use of five travel modes (i.e., single-occupant vehicles, carpooling, public transit, biking, and walking) for both work and non-work trips. Two of these groups are more car-oriented and less multimodal (i.e., drive-alone users and carpoolers), whereas the other two are less-car-oriented and display a higher level of multimodality (i.e., transit users and cyclists). Results from this study reveal the unique profile of each traveler group in terms of their sociodemographic characteristics and built-environment attributes. This study further investigates the different characteristics of each traveler group in terms of ridehailing adoption, trip frequency and trip attributes. Transit users are found to have the highest rate of ridehailing adoption and usage. They are also more prone to use pooled ridehailing services in comparison to other groups. Lastly, in terms of mode substitution, were ridehailing not available, respondents tend to choose the mode they use most frequently. In other words, car-based travelers are more likely to substitute ridehailing trips with car trips, whereas non-car-based travelers are more likely to replace ridehailing with less-polluting modes. Findings from this study will prove valuable to transit agencies and policymakers interested in studying how ridehailing can be integrated with other modes and how they can promote more multimodal and less car-dependent lifestyles.

5.2 Background and Introduction

An extensive recent body of work has delved into the research on understanding how ridehailing services impact mobility and travel patterns, yet findings remain inconclusive. One strand of literature suggests that ridehailing could fill the travel gaps for non-vehicle households or those previously excluded by the taxi industry (Brown, 2019; Circella et al., 2018; Wu & MacKenzie, 2021), substitute private vehicles (Henao & Marshall, 2018; Zou & Cirillo, 2021), and complement public and active transportation (Conway et al., 2018; Feigon & Murphy, 2018; Henao & Marshall, 2018; Sikder, 2019). On the contrary, several studies draw the opposite conclusion, suggesting that ridehailing has increased vehicle miles traveled, road congestion and greenhouse gas (GHG) emissions (Erhardt et al., 2019; Henao & Marshall, 2018; Wu & MacKenzie, 2021), while driven down the ridership of public transit (Diao et al., 2021; Hall et al., 2018; Tang et al., 2019). There are also studies suggesting the complementarity and substitution effects of ridehailing on various modes co-exist (Rayle et al., 2016; S. A. Shaheen, 2016; Young et al., 2020).

Previous studies, however, often implement behavior survey and investigate ridehailing trip on a one-off basis by asking respondents to recall and self-report information on their last ridehailing trip solely (Circella & Alemi, 2018) or at best within the context of one day of travel (Wu & MacKenzie, 2021). This method is prone to recall errors and biases, but more importantly, it overlooks the "inertia effects" of travel decisions, the latent tendency of using (or not using) certain means of travel on a regular basis (Vij et al., 2013). A multi-day observation is required to capture a realistic representation of both the variability and the stability of individuals' modality style (Buehler & Hamre, 2015; Kuhnimhof et al., 2006; Nobis, 2007). There are a few studies on ridehailing, though not in the US context, that utilized multi-day passively collected global positioning system (GPS) trajectory data of ridehailing trips, but researchers were either not able to link the trip data with rider profiles to perform individual-level analyses (Li et al., 2019) or not able to incorporate ridehailing into multimodality analyses broadly (Chen et al., 2021).

This study aims to fill in those gaps by investigating the interrelationships among ridehailing use, travel patterns and multimodality using a week-long (consecutively observed) GPS-based trip diary dataset collected from four metropolitan regions in the State of California during 2018 and 2019. The data incorporates both passively collected GPS tracking data and actively collected questionnaires, which together are expected to capture more complete mobility patterns of individuals, with reduced biases or errors associated with recall-based surveys. The study consists of two objectives: (1) using a latent class cluster analysis (LCCA) to identify distinctive traveler groups with unique trip profiles (i.e., weekly trip frequency by modes) and personal characteristics in a sample of 5,053 commuters; (2) investigating the association between multimodality and ridehailing adoption/usage and examine ridehailing trip attributes (e.g., when, where, and for what purpose) for traveler groups with distinctive forms of multimodality.

5.3 Methods

Latent class analysis (LCA) is commonly used in transportation research to identify unique traveler groups (de Haas et al., 2018; Molin et al., 2016; Ton et al., 2020). To investigate the ways that individuals' modality is associated with their use of ridehailing (and potential impacts to the environment), a latent-class cluster analysis (LCCA) is employed. LCCA assumes that a given sample consists of multiple latent classes with unique characteristics, without information about the class of individual cases. Thus, LCCA estimates the probabilities of individual cases belonging to one class or another, instead of deterministically assigning them to a specific class (Buehler & Hamre, 2015). In addition, unlike random-parameter models (e.g., mixed logit), which require to assume a priori distributions for parameter estimates, LCCA models heterogeneity without such a strong assumption (Vermunt & Magidson, 2002). In LCCA, two sub-models are simultaneously estimated. First, the measurement model estimates parameter estimates for the class-specific distribution of selected indicators, which helps us uncover the multiple forms of heterogeneity in a sample. Second, the structural model specifies the relationships in which individuals' attributes (i.e., active covariates) are associated with their probabilities of belonging to one class or another.

Weekly trip counts for five travel modes (i.e., SOV, carpool, transit, biking, and walking) for both work and non-work purposes are used as indicators for classifying individuals into latent classes. It is important to note that "TNC" is excluded from this initial step, but the characteristics of ridehailing trips are examined and compared in greater detail once the latent classes have been identified. Namely, these ridehailing trip attributes will be considered as "inactive" covariates. "Active" covariates, which were incorporated into the structural model, include the socioeconomic factors, demographic characteristics, transportation subsidies, and land-use attributes that pertain to individuals. To the best of the authors' knowledge, this study is the first to incorporate trip frequency as count variables under the structure of LCA, which offers a more realistic and accurate representation of trip data than previous studies that regard trips as continuous variables (Lee et al., 2020).

5.4 Results

5.4.1 Four Distinctive Traveler Groups

After estimating models with latent classes, a four-class solution is chosen as the optimal based on goodness-of-fit measures and interpretability. These measures include Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC), Adjusted BIC (ABIC), and the likelihood $\chi 2$ statistic. Lower values of the AIC, BIC and ABIC demonstrate better fit, while higher values of entropy indicate better class separation (Collins & Lanza, 2010; Goulias & Henson, 2006).

The four traveler groups with distinctive average one-week trip frequency by various travel modes for both commuting and non-commuting purposes, based on which each class is named. It is found that among these four groups, two of them are auto-oriented users (Class 1 and Class 2, which together accounts for more than 80% of the sample) while the other two are less-auto-oriented users (Class 3 and Class 4, which together accounts for the remaining 19%).

Class 1, Drive-alone Users (53.0%), have significantly higher trip frequencies and vehicle miles traveled (VMT) by SOV and for both work and non-work trip purposes. However, their usage of public transit and active modes is relatively minimal. ***Class 2, Carpoolers (27.9%)***, predominantly use carpooling, especially for non-work trips. ***Class 3, Transit Users (14.8%)***, engage in the highest number of transit and walking trips, while maintaining the lowest frequency of car-based trips. Notably, their non-work walking trip frequency is the highest among all trip types. As explained, the smartphone GPS tracking app can identify short-distance walking trips more accurately, which explains the relatively high number of walking trips, despite their cumulative trip distance still remaining low. Additionally, since walking can be identified as the access/egress mode of transit trips, transit users and pedestrians are identified together in one class, rather than grouping cyclists and pedestrians as "active users" as is typically done in previous studies. Finally, ***Class 4, Cyclists (4.3%)***, have the highest frequency of biking trips compared to other groups, alongside a moderate number of trips using all other modes. Consistent with previous findings, automobiles and transit remain important components for cyclists when bicycling is not a suitable option (Kuhnimhof, Chlond, & Huang, 2010). Evidently, transit users, and cyclists are more multimodal than car users, showcasing a more balanced distribution of trip frequency and distance across various modes.

Drive-alone users primarily consist of individuals aged 35 or older (71%). This class has a high proportion of full-time employees. As expected, respondents in this class are mainly drivers and have the highest number of vehicles per household worker, which explains their frequent reliance on driving alone. In fact, this class has the highest share of individuals living in low-density home locations and working in low-job-density working locations. Interestingly, lower job density is also apparent in their home locations (this variable is not included in the model because of high multicollinearity), suggesting a higher chance of worker-job mismatch, which explains their high reliance on automobiles for work purposes. Overall, the profile of this group aligns with the profile of "monomodal drivers" identified in previous papers (Lee et al., 2020; Ralph, 2017).

Carpoolers, on the other hand, tend to be younger, with 61% of individuals aged under 35. They have the least vehicles and the highest proportion of individuals without a driver's license. This explains their extensive use of carpooling, particularly for non-work trips. In comparison to *Drive-alone users*, *Carpoolers* are more likely to live in densely populated areas and work in areas with high job density.

The profile of ***Transit users*** is notably different from that of ***drive-alone users***. They are the least car-dependent group among all the classes. ***Transit users*** and ***Cyclists*** share some similarities, but also have distinguishing characteristics. While *Transit users* have the least proportion of Caucasians (18%), *Cyclists* are in fact, predominantly Caucasians (39%)[6]. Similarly, *Transit users* have a higher representation of females, whereas *Cyclists* have a higher proportion of males. This disparity may be influenced by factors such as the physical demands and perceived risks associated with cycling. Moreover, *Cyclists* tend to have higher education and income levels compared to *Transit users*. Finally, *Cyclists* are also more likely to work in areas with high job density, which usually an indicator of a more diverse land use and better transportation infrastructure. This aligns with existing studies that highlight the positive association between higher-density built environments and less auto-oriented lifestyles (Chowdhury & Scott, 2020; Schneider, 2015).

5.4.2 Trip Characteristics by Classes

With a better understanding of the profiles of each of the four identified traveler groups, the distinct characteristics of ridehailing trips among these groups can be explored. A total of 3,964

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[6] One counterintuitive observation regarding race is the absence of any Black or African Americans within *Transit user* group. This may be attributed to two main reasons: (1) this race group is underrepresented in the original dataset, and the weighting process may not have fully adjusted for the discrepancy between the sample and the target population. According to the technical document outlining the weighting process, some deviations were observed in each region (e.g., a -16.30% deviation in SF other regions); (2) upon inspecting the data, it became apparent that compared to other race group, very few observations from this race group had completed the complete 7-day survey, which is the basis of this study.

unweighted TNC trips are observed among individuals included in the analysis. However, this number was adjusted to 1,839 trips after applying weights, as both surveys had intentionally oversampled TNC trips. Table 5 provides class-specific probability-weighted summary statistics for TNC trips during the survey period. 39% were made by Class 3, which consists of transit users and pedestrians. Carpoolers, cyclists, and drive-alone users accounted for 33%, 28% and 9% of the TNC trips, respectively. Transit users are more likely to be TNC users, as reflected in both self-reported monthly ridehailing travel frequency and the number of TNC trips observed during the survey period. Consistently, transit users have the highest average one-week ridehailing trip frequency. Regarding the type of ridehailing service used, transit users are more likely to use pooled ridehailing, while drive-alone users are more inclined to use regular, economy, and premium services. Drive-alone users also tend to schedule their trips in advance for a specific pick-up time.

In terms of temporal patterns, drive-alone users are more likely to take ridehailing trips during weekends compared to other groups. Although most ridehailing trips across all classes start in the afternoon and evening, transit users are more likely to travel in the morning and midday periods compared to the average. On the other hand, car users tend to take their trips in the afternoon, evening, and late night. These differences in timing appear to be related to trip purposes. For instance, transit users and cyclists are more likely to use ridehailing for mandatory trips (e.g., commuting), while car users are more likely to use it for recreational purposes later in the day. Moreover, while only around 3% of all ridehailing trips in the sample were directly connected with transit, transit users show higher proportions (5% and 7%) of TNC trips starting and ending with a travel mode switch, indicating that TNC is more likely to be the access/egress mode for them.

Finally, if ridehailing services were not available, individuals from different classes would have chosen different means of travel. The findings suggest that individuals within each traveler group would very likely have chosen the mode that is most commonly used within their respective group. For instance, if ridehailing was not an option, car users would likely have taken taxis, driven their own cars, or shared rides with others, transit users would still prefer transit as their primary alternative (Tarabay & Abou-Zeid, 2020). However, cyclists would likely ride with others.

Table 5 TNC user distribution and trip characteristics by classes

	Class 1 Drive-alone users	Class 2 Carpoolers	Class 3 Transit users	Class 4 Cyclists	Sample average
Weighted n	2678	1410	750	215	5053
Weighted %	53%	28%	15%	4%	100%
Number of weighted TNC trips by each class	516	602	721	160	1839
% of total weighted TNC trips in the sample	28%	33%	39%	9%	100%
TNC user group (based on self-reported monthly TNC usage frequency)					
Non-user (less than 1 day per month)	**63%**	49%	39%	51%	57%
Occasional users (1-3 days per month)	35%	**43%**	25%	**43%**	37%
Frequent users (4+ days per month)	2%	8%	**35%**	6%	6%
TNC user group (based on observed one-week trip frequency in travel diary)					
Non-user (0 times per week)	**93%**	75%	49%	83%	85%
Users (1 time per week)	2%	**7%**	**7%**	4%	4%
Users (2-3 time per week)	5%	14%	**22%**	12%	8%
Users (4+ time per week)	1%	4%	**21%**	1%	3%
Average one-week TNC trip frequency					
Among entire sample from 4 MPOs	0.19	0.43	**0.96**	0.74	0.40
TNC service type (only in 3 MPOs)					
Pooled (e.g., UberPOOL, Lyft Line)	11%	27%	**37%**	36%	28%
Regular or economy (e.g., UberX, Lyft)	**87%**	65%	62%	64%	69%
Premium (e.g., UberSELECT, Lyft Premier)	**0.6%**	0.5%	0.2%	0.01%	0.4%
Unknown	1.4%	**6.9%**	0.4%	0.01%	2.6%
Scheduled TNC trip in advance for a specific pick-up time (only in 3 MPOs)					
No	96%	97%	**99%**	97%	97%
Yes	**4%**	3%	1%	3%	3%
Day of the week					
Weekday	62%	77%	73%	**83%**	72%
Weekend	**38%**	23%	27%	17%	28%
Time of the day					
Morning (5 am – 10 am)	12%	**25%**	20%	12%	19%
Midday (10 am – 3 pm)	7%	19%	**24%**	20%	18%
Afternoon (3 pm – 7 pm)	21%	**24%**	**24%**	37%	24%

	Class 1 Drive-alone users	Class 2 Carpoolers	Class 3 Transit users	Class 4 Cyclists	Sample average
Evening (7 pm – 11 pm)	**42%**	23%	22%	10%	27%
Night (11 pm – 5 am)	18%	9%	9%	**21%**	12%
Activities at TNC trip origin					
Home	**37%**	30%	27%	19%	30%
Mandatory	7%	18%	22%	**28%**	17%
Recreation	**45%**	35%	33%	25%	36%
Maintenance/escort/errand/other	9%	10%	13%	**27%**	12%
Changing travel mode	1%	7%	5%	0%	4%
Activities at TNC trip destination					
Home	31%	26%	36%	**44%**	33%
Mandatory (school/work trips)	9%	**34%**	24%	5%	22%
Recreation	**47%**	24%	26%	25%	31%
Maintenance/escort/errand/other	11%	9%	7%	**26%**	10%
Change travel mode	2%	6%	**7%**	0%	5%
Alternative means of travel were ridehailing not available					
Would make same trip by using a taxi	32%	**35%**	22%	14%	28%
Would make same trip by driving own car	**38%**	24%	7%	1%	19%
Would make same trip by riding with others	13%	8%	3%	**66%**	12%
Would make same trip by using transit	5%	16%	**39%**	3%	21%
Would make same trip by walking/biking	5%	9%	**12%**	11%	9%
Would travel to a different place instead	0%	1%	2%	**4%**	1%
Would NOT make trip at all	4%	4%	**16%**	0%	8%
Other	1%	**4%**	1%	1%	2%

Note: **Bold** values in the table indicate the highest value for each row.

6 Modal Substitution and Induced Travel of Ridehailing

6.1 Abstract

The availability of ridehailing services, such as Uber and Lyft, affect the way people choose to travel and, in some instances, enable travel opportunities that were previously suppressed, leading to additional trips. Previous studies have investigated the modal substitution and induced travel caused by ridehailing, yet few have investigated the factors associated with these travel behaviors. Accordingly, this study examines the personal and trip characteristics associated with ridehailing users' decisions to substitute other modes of travel or conduct new trips by ridehailing. Using detailed survey data collected in three metropolitan regions of California in 2018 and 2019, an error components logit model is estimated to analyze ridehailing users' choice of an alternative travel option if ridehailing services were unavailable. It is found that over 50% of ridehailing trips in the sample are replacing more sustainable modes (i.e., public transit, active modes, and carpooling) or are creating new vehicle miles, with a 5.8% rate of induced travel, and public transit being the most frequently substituted mode. Several factors are also found that influence travel induced by ridehailing and the substitution of ridehailing for transit and active travel. Respondents without a household vehicle and those who use pooled services instead of solo ridehailing services are more likely to replace transit. Longer-distance ridehailing trips are less likely to replace walking, biking, or transit trips. Trips for leisure and at night are the most associated with travel induced by ridehailing. Respondents identifying with an underrepresented racial or ethnic minority or lacking a household vehicle are less likely to cancel a trip were ridehailing unavailable, suggesting their use of ridehailing for essential rather than discretionary purposes. Together, these findings provide valuable insight to policymakers seeking to address the environmental and equity issues associated with ridehailing in California.

6.2 Background and Introduction

The growth of ridehailing creates both challenges and opportunities for the urban areas where TNCs mostly operate, particularly in terms of modal substitution and complementarity. Proponents of ridehailing claim many benefits could be derived if most people share rides instead of driving their own cars, including energy savings, less space devoted to parking, and lower levels of pollutant and greenhouse gas (GHG) emissions (Shaheen, 2018). Some studies have also found that ridehailing complements public transit by providing a first-mile/last-mile mode to bus and rail travelers (Hall et al., 2018). On the other hand, there is evidence that the existence of ridehailing has tended to decrease transit ridership in the United States (Graehler et al., 2019). A drop in transit ridership in favor of ridehailing will increase vehicle miles traveled (VMT) and decrease revenue for transit companies, which may lead to a cycle of decline in transit services. Although there are multiple results on the rates of substitution of ridehailing for other modes in various cities, relatively few previous studies have modeled the effects of people's personal traits or the kinds of trip they make on modal substitution of ridehailing.

Ridehailing provides the convenient door-to-door mobility of car travel without needing to own a car and, compared to traditional taxi trips, ridehailing trips can have much shorter waiting times (Rayle et al., 2016). Therefore, this relatively new mode may provide people with more travel opportunities and motivate trips that would not have occurred were ridehailing not available, i.e., induced travel. Compared to other types of shared mobility, Jiao et al. found that the use of a ridehailing app was associated with more daily trips by respondents to the 2017 National Household Travel Survey (NHTS) (Jiao et al., 2020). Most studies that have investigated induced travel of ridehailing have been limited to a descriptive statistical analysis and there has been little research into the factors that influence induced travel of ridehailing.

6.3 Methods

The purpose of the present investigation is to uncover the personal and trip characteristics associated with ridehailing users' decisions to substitute other modes of travel or conduct entirely new trips with ridehailing. To this end, a model of ridehailing users' choice of an alternative travel option were ridehailing not available is designed. This model is estimated on survey data collected in the three metropolitan regions of California in the 2019 TNC study, as described earlier. This unique dataset captures the daily trip records and sociodemographic characteristics of a large, random sample of ridehailing users, and enables us to overcome some of the limitations of previous studies on modal substitution and induced travel of ridehailing. The choice of an alternative travel option depends on multiple characteristics of the decision maker and the trip. The following paragraphs describe the choice set and explanatory variables and specify the discrete choice model.

The dataset contains ridehailing users' responses to the question: "If Uber, Lyft, or similar services did not exist at all, how would you have made this trip?" From the categorical response variable, an initial choice set is created consisting of eight alternatives: private car, carpool, taxi, active travel (biking/walking), transit, no travel, different destination, and a general category for options that were not enumerated in the survey. However, due to low response rates (less than 2% for "different destination" and less than 3% for the "other" category), the latter two alternatives are grouped together to create a choice set of seven items.

Multiple personal characteristics of the ridehailing users are included in the model. A set of dummy indicator variables encode the study areas, with the MTC/SFCTA region as the reference case, i.e., the effects of residence in the SANDAG or SCAG regions are estimated relative to residence in the MTC/SFCTA region. The age of an individual is encoded by a set of dummy variables for three age categories: 18–34, 35–54 and over 55 years old, with the youngest age range as the reference case. Persons under 18 are not allowed to order a ridehailing service and are therefore excluded. Five racial and ethnic groups are considered: Asian or Pacific Islander; Black or African American; Hispanic, Latino, or Spanish Origin; White; and a group for other racial and ethnic minorities with very small sample sizes in the dataset. A total of 29 individuals identified as American Indian or Alaska Native, 25 individuals identified as Middle Eastern or North African, and 41 individuals self-identified as another race or ethnicity; however, their specific identities are not included in the dataset. Some of these individuals also identified as Latino, Hispanic, or Spanish Origin and are included in that group. An individual's racial or ethnic group is encoded by a set of dummy variables, with White non-Hispanic as the reference case. Employment status is also encoded by a set of dummy variables, including full-time employment, part-time employment, self-employment, and a composite status of unpaid intern/volunteer/unemployed. Full-time employment is the reference case. The adjusted household income is calculated based on household composition, according to the U.S. Census Bureau equivalence scale (Census Bureau, 2021), and regional cost of living based on the Bureau of Economic Analysis Price Parity Index (Bureau of Economic Analysis, 2020). The adjusted household income of the set of ridehailing users is then divided into quartiles to create a set of dummy variables, using the third quartile as the reference case. An individual's lack of access to a household vehicle is encoded by a single binary indicator variable that equals 1 if they specify zero household vehicles and 0 otherwise. The dataset consists of people who identify as female, male and non-binary (or prefer to self-describe), the latter of which accounts for less than 1% of respondents. A binary variable is created that equals 1 if the individual identifies as male and 0 otherwise.

Trip characteristics are also included in the model. Trip distance is measured in miles. A binary variable indicates whether a trip is offered by a pooled ridehailing service, even if the trip was not matched. A set of dummy variables encodes three traveling party sizes: a lone traveler, two passengers, and three or more passengers, with lone trips as the reference case. In terms of purpose, recreational trips, home trips, and trips to work or school comprise the majority of ridehailing trips in the dataset. Therefore, trips for changing mode, errands, escorting others, and shopping are grouped into a single category and create a set of dummy variables with home trips as the reference case. The departure time is discretized into five periods of the day: morning (5:00 AM–9:59 AM), midday (10 AM–2:59 PM), afternoon (3:00 PM–6:59 PM), evening (7:00 PM–10:59 PM), and night (11 PM–4:59 AM) and create a set of dummy variables with evening as the reference case. Finally, alternative-specific constants are specified for the members of the choice set, with transit as the reference case, which capture the effects of unobserved factors that may influence the choice of an alternative travel option.

An error components logit model is specified for the choice between alternative travel options for a ridehailing trip, were the ridehailing service not available, following the approach of Hess et al. (Hess et al., 2008). For each individual and alternative in the choice set, the model of the utility of the alternative includes a standard normally distributed random error component. To account for repeated choice observations of the same individuals, when calculating the log-likelihood, integration is performed over the error components at the individual level, which in turn captures the correlation across choices for the same individual over time.

The error components logit model specified above is estimated using a simulated maximum likelihood estimation with 100 modified Latin hypercube sampling (MLHS) draws, as suggested by Hess et al (Hess et al., 2006) for the error components. The model estimation was carried out using the R Apollo package (Hess & Palma, 2019, 2021).

6.4 Results

Out of the 7,333 ridehailing trips in the sample, there is a 5.8% rate of induced travel (i.e., rides that would not have occurred were ridehailing services not available). Among trips that would have occurred regardless of whether ridehailing was available, the most substituted modes were transit, taxi, and private car, respectively. These results match the general trend in the literature on modal substitution and induced travel of ridehailing (Tirachini, 2020). Active travel was the next most substituted mode, followed by carpooling, while other modes/different destination comprised the smallest percentage of responses.

Figure 5 shows the observed substitution rates of ridehailing for the alternative travel options in the choice set. When considered conjointly, over 50% of ridehailing trips are replacing more sustainable modes (i.e., transit, active mode, and carpooling) or creating new vehicle miles, which strongly suggest that this new form of travel may be responsible for an increase in transportation related GHG emissions.

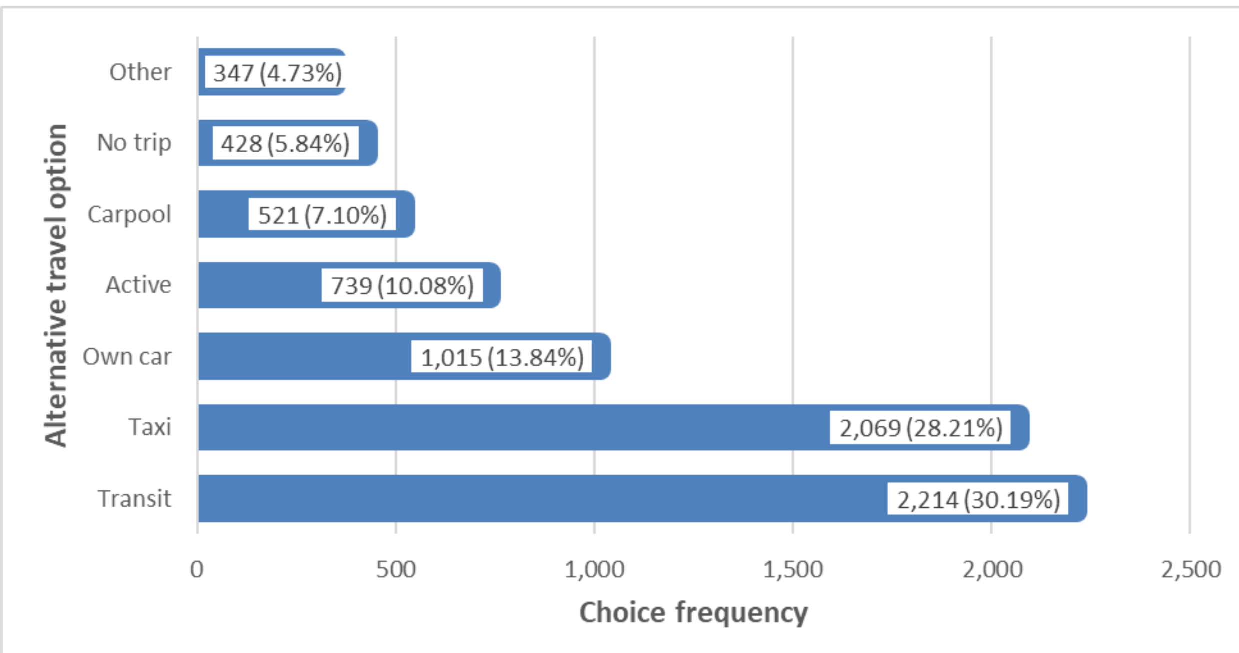

Figure 5 Observed substitution rates of ridehailing for the alternative travel options in the choice set

The results of the final model i.e., the effects of personal and trip characteristics on modal substitution and induced travel of ridehailing, respectively, are explained below. Being from a carless household is negatively associated with other substituted modes relative to the reference mode, which is transit. Accordingly, it is found that people from carless households are more likely to substitute ridehailing for public transit than car owners, which is consistent with findings from Gehrke et al. (2019). Residents of the MTC/SFCTA region are the most likely to substitute ridehailing for public transit, which makes sense due to the extensive transit network in the San Francisco Bay Area. The SANDAG region appears to have the greatest association with private car, carpool, and taxi travel in the absence of ridehailing, which suggests that ridehailing may be more competitive with other car-based modes in this region than the others. Compared to those aged 18–34, people aged 55 and above are less likely to substitute ridehailing for active trips than public transit ($p < 0.01$). They are also more likely to take a taxi ($p < 0.001$) than use transit in the absence of ridehailing. In the absence of ridehailing, respondents of Hispanic, Latino, or Spanish Origin are less likely to drive their own car or take a taxi than their White, non-Hispanic counterparts ($p \approx 0.01$), while those identifying as Black, African American, or other small racial and ethnic minority groups are less likely to pursue active travel than White respondents ($p \approx 0.01$). Part-time employees are less likely to substitute ridehailing for private car or taxi travel than full-time employees ($p < 0.1$). People at or below the sample's median household income are less likely to substitute ridehailing for active travel and taxi trips than public transit, compared to higher-income people. The results from Mahmoudifard et al. (2017) also indicate that ridehailing users with higher income are more likely to drive or take a taxi trip in the absence of ridehailing.

In terms of trip characteristics, trip distance is positively associated with the replacement of carpooling ($p < 0.1$) and negatively associated with the replacement of active travel ($p < 0.001$). Gehrke et al. (2019) also found that longer trips predict the replacement of vehicle-based modes in Boston, and shorter distance trips are more likely to replace active travel. To provide additional context for this finding, the proportions of alternative travel options that were chosen at various distance intervals are analyzed. The proportion of trips that would have been made by active travel declines significantly beyond one mile and further drops at the five-mile mark to around 1% or fewer of the responses. In contrast, the proportion of trips that would have been made by carpooling doubles at the five-mile mark to almost 12%. From a quarter to a third of trips would have been made by taxi in the absence of ridehailing across all distance intervals, while slightly more would have been made by transit in all but the shortest and longest distance intervals. For trips under one mile, the waiting time for transit likely dominates the travel time and makes this option less attractive. For trips between 20 and 50 miles, over 50% would have been made by either taxi or driving one's own car if ridehailing services were not available.

Pooled ridehailing services substitute transit more than carpooling ($p = 0.001$), taxi ($p < 0.001$), and private car trips ($p < 0.1$). These results further match those from Gehrke et al. (2019). Trips made at the weekend rather than on a weekday are more likely to be made by taxi in the absence of ridehailing ($p < 0.01$). Respondents traveling alone are less likely to replace a taxi trip than those traveling with others ($p \approx 0.01$). Compared to lone travelers, parties of 3 or more are more likely to carpool in the absence of ridehailing. Individuals traveling with one other person (total of two travelers) are the most likely to drive their own car in were ridehailing unavailable, while those traveling with two or more others are the most likely to carpool with someone else. These results show that ridehailing services are effectively competing with other modes for group travel. The trip purpose and start time are also found to have a significant effect on modal substitution. Ridehailing trips conducted for leisure purposes are most likely to replace private car ($p < 0.000$) and active trips ($p < 0.1$). Compared to trips returning home, leisure trips and trips for errands or changing mode are more likely to be made by carpooling or taking a taxi than transit ($p < 0.1$). Ridehailing is more likely to substitute taxi trips in the evening than during earlier parts of the day and is most likely to replace both carpool and taxi trips at night. This can partially be explained in prior work by Tirachini (2020) who found that many people prefer to use a ridehailing service to return home at night instead of asking a relative to pick them up. Ridehailing also appears to substitute active travel at night ($p < 0.1$). The substitution of ridehailing for private car trips is positively associated with morning and afternoon travel ($p < 0.1$), which may be due to commuting to and from work at those times of day.

Lacking a household car predicts less travel induced by ridehailing relative to substituting transit ($p < 0.1$). Compared to the MTC/SFCTA region, residence in SANDAG or SCAG is associated with more travel induced by ridehailing ($p < 0.01$). Underrepresented racial and ethnic minorities are less likely than White non-Hispanic respondents to have induced travel by ridehailing ($p < 0.1$), as are part-time employees ($p < 0.01$) compared to full-time employees. Individuals in these segments of the population may use ridehailing for essential purposes rather than for discretionary trips. Neither gender nor income level seems to influence travel induced by ridehailing.

Trip distance, the use of a pooled ridehailing service, and the size of the travel party do not have a significant effect on induced travel. As expected, trips for leisure purposes are the most associated with travel induced by ridehailing ($p < 0.001$). Trips to work or school are less likely to be discretionary and are therefore not associated with much induced travel. It should be noted here that some of the induced trips for various purposes have an associated return trip home that would also not occur in the absence of ridehailing, which in turn may explain why it is expected to see some induced travel for home-based trips. Induced travel of ridehailing is less likely to occur in the morning or afternoon periods compared to other parts of the day ($p = 0.005$) and is most likely to occur at night ($p < 0.000$). Tirachini (2020) highlights the utility of ridehailing for nighttime activity engagement due to its perceived safety and convenience.

7 Factors that Affect the Use of Pooled Ridehailing Services

7.1 Abstract

Pooled ridehailing services (e.g., UberPOOL) hold promise for a future with less vehicle travel but more passenger travel, assuming that these services do not lead to additional mileage caused by deadheading or detours to pick up and drop off additional passengers sharing the rides. In this chapter a mixed logit model is used to study the factors that affect the choice between pooled and solo ridehailing (e.g., UberX) trips using the TNC survey panel data collected in the MTC and SFCTA, SANDAG, and SCAG California metropolitan areas to understand the demand for pooled ridehailing services. As explained earlier in this report, the data were collected through rMove, an in-app survey and GPS data collection tool used to collect revealed preference data on users' travel behaviors. It is found that lower-income individuals, non-white minorities, females, and younger adults are more likely to choose pooled ridehailing. Trips that originate in high-density areas are also more likely to be pooled. Being a frequent ridehailing user is associated with more pooling, whereas not having to pay for a trip (e.g., a work trip paid for by an employer) reduces the likelihood of pooling. A positive relationship is found between the use of public transit and active modes and the likelihood of pooling, which highlights the risk of competition (and substitution) among these modes, but in turn may highlight an openness for multi-modal travel among certain groups. Further, and somewhat unsurprisingly, the more cars individuals own, the less likely they are to pool. Policymakers, such as those involved with the CMS in California, will find value in this analysis as they seek to expand the share of pooled ridehailing trips, while mitigating deadheading, in an effort to reduce the emissions and congestion associated with the TNC industry.

7.2 Background and Introduction

The California TNC fleet has a 7% lower passenger occupancy than the statewide passenger vehicle fleet, and data show that TNC vehicles have only one passenger for 61% of their VMT; higher occupancy could significantly reduce the gCO2/PMT for these mobility services (CARB 2019).

Pooled (shared) ridehailing (e.g., UberPOOL, LyftLine), where multiple passengers share the vehicle for all or a portion of the ride, can significantly increase the average vehicle occupancy of TNC trips and thus play an important role in mitigating ridehailing impacts on congestion and GHG emissions (Hou et al. 2020). Although pooled rides are offered at a lower cost than traditional "solo" trips (e.g., UberX), data show that most Uber and Lyft rides are conducted entirely alone and that the pooled market share, to date, remains quite low (Hou et al. 2020; Alonso-González et al. 2020). For this reason, in this study the focus is on investigating what are the factors that make pooled ridehailing unsuccessful in comparison with its solo version, with the goal of creating useful insights into ways that could increase the use of pooled TNCs in the future.

The factors that influence the choice to use pooled ridehailing trips over non-shared (i.e., solo) ridehailing trips are investigated using data collected via a travel diary in the pre-pandemic time (between November 2018 and November 2019) in three regions in the state of California: the MTC and SFCTA, SANDAG, and SCAG. As explained earlier in this report, the travel diary was collected over a 7-day period via the *rMove* app that passively collected the respondents' ridehailing trip data (as well as trips made with other modes) and actively asked participants additional survey questions pertaining to their trips at the end of each trip and day.

This study expands the knowledge about why pooled ridehailing is unsuccessful in comparison to solo ridehailing. Furthermore, such investigation relies on a unique set of data that simultaneously provides information on the respondent's travel behavior -- via passively recording very detailed information on their trips -- and their trip experience by actively asking questions via a survey component at the end of each trip/day. This study is also valuable to policymaking in the field of sustainable transportation such as those involved with the implementation of CARB's Clean Miles Standard and paves the way for similar regulations in other U.S. states and around the world. For instance, policymakers may consider including *occupancy-based* regulations to discourage single-passenger rides, while exempting pooled ridehailing from new road pricing schemes. In addition, employers could adopt pooled ridehailing as the default option for business-related trips, which is currently rarely done.

7.3 Methods

In this study the research team focused exclusively on passengers that choose ridehailing for their travel. The team considers the effect of a set of independent variables (discussed later in this section) on the dichotomous choice between pooled (1) vs. solo ridehailing (0 or reference) across multiple trips (i.e., repeated choices). A mixed logit (ML) model is used to investigate the choices of individuals to use pooled or non-pooled (solo) ridehailing services. The following paragraphs describe the dependent and independent variables.

Dependent variable: To study the decision to use pooled vs. solo ridehailing, the research team only retained solo trips with a party size of two passengers or less, as omitting to do so would prevent from making direct comparisons with pooled ridehailing trips which can only be booked for two passengers. Indeed, ridehailing providers cap the number of bookings per pooled ride to two people to ensure the ability for the trip to be matched with other passengers. The research team used 5,136 trips done by 1,991 participants across the three regions in California. Most of the respondents are residents of the San Francisco Bay-Area (69.1%), 17.5% live in the San Diego region, and 13.5% in the counties of Los Angeles and Orange. 63.5% of the sample trips are solo ridehailing and 36.5% were pooled.

Independent variables: The research team included the TNC use frequency to investigate the likelihood of using pooled ridehailing services based on the number of times a user uses a TNC platform. Other variables include an indicator of traveling with friends or family, and the respondents' mobility profile, e.g., whether the participant typically drives a car. The mobility profile variables are constructed in the following way: for each respondent the total number of trips made with each mode during the travel diary period is calculated (e.g., how many times participant X partook in a car trip during the travel diary) and then divided by the number of completed days in the participant's travel diary (not all respondents completed 7 full days of their travel diary). This ratio represents a "weight" per respondent per mode, that is indicative of respondents travel behavior. Following this approach, one mobility profile variable is created per mode: "car", "walk", "bike", "transit", and "taxi". Also included in the model are socio-demographic attributes such as age, gender, race, household income, and student status. A trip purpose variable is included, specifically if the trip's destination purpose is home, work/school, leisure, errands or to a transportation hub to catch another transportation mode. The effects of the time of the week (whether the trip takes place on a weekend or a weekday) and time of the day are also analyzed, for which the classification from Young & Farber (2019) is used. The type of payment (e.g., whether the participant paid for the full amount or someone else paid for it) and its effect on the selection of ridehailing trips is also measured. The duration of the trip as recorded by the *rMove* app is also used in the model. Built environment variables are acquired from the decennial U.S. Census and American Community survey using the Census API in R, with population and job density variables (the number of residents and jobs per square mile) based on the centroid coordinates of the block-groups of the origin and destination of the trip. In this study, only the population density at the origin of the trip was used to avoid multicollinearity issues that were found to be high among the built environment variables. Population density is discretized at the origin of the trip into two categories: anything above the median is considered "dense" environment and anything below the median "non-dense".

A cross-tabulation analysis revealed that most of the explanatory variables are significantly associated with the responses. However, the next section only discusses the variables that resulted to be significant in the final version of a mixed logit model.

7.4 Results

This section discusses the results from modeling the choice to use pooled or solo ridehailing using the independent variables mentioned above. Evidence is found that confirms the finding from (Shaheen et al., 2021) that those who use TNC more frequently (at least once a month or more) are more likely to choose pooled ridehailing. This may be linked to them having more situations to pool, perhaps in central parts of cities, or being more prone to shared forms of mobility. Similarly, there is a negative association between traveling with friends or family and the likelihood of using pooled ridehailing services that confirms the results from (Lavieri & Bhat, 2019b). This may be explained by the price advantage of pooling being lessened if the trip is already shared to begin with. The results also show that those whose ride is paid for by their employer (or by someone else) are less likely to choose the pooled ridehailing option. This is intuitive as pooling requires longer travel time and business travelers need to get somewhere in a fast way. Although this should be further articulated, this finding is insightful as companies could easily contribute to decarbonization objectives by introducing pooling as the default travel mode for work trips instead of solo ridehailing, perhaps supported by a form of "clean" carbon credits.

In line with Shaheen et al., 2021, it is found that individuals' mobility profile plays a critical role on the choice of pooling ridehailing; the data show that respondents who integrated public transit or biking in their travel routine are more likely to use pooled ridehailing. As opposed to (Shaheen et al., 2021) the sample shows that trips ending at home are more likely to be pooled vs. trips done for leisure errands, or to catch another transportation mode, which might indeed come with more urgency. This in turn, may prevent some users from choosing the more time-consuming pooled ridehailing service; not to mention it often also being characterized by uncertain arrival times. On the other side, the present research confirms the findings of (Alonso-González et al., 2020) and (Lavieri & Bhat, 2019b) that leisure trip-purpose reduces the likelihood of choosing to pool a ride.

As reported by (Hou et al., 2020), the present results confirm that the longer the trip duration, the higher the likelihood to use pooled ridehailing. This might be because longer rides are more expensive, and the cheaper pooled option therefore becomes more appealing, or, more simply, because pooled rides are more time consuming. Confirming the findings of (Brown, 2019; Hou et al., 2020; Kang et al., 2021) trips originating in dense urban areas are more likely to be pooled in comparison to those that start in non-dense areas. Owning private vehicles is associated with lower chances of pooling. In addition, similarly to (Kang et al., 2021) White respondents are less likely to pool as compared to non-White individuals, who represent the minority in the sample. It is observed that the lower- and middle-income groups (Brown, 2019; Clewlow & Mishra, 2017; Shaheen et al., 2021) and younger individuals (Ze et al., 2019) are more likely to pool. As opposed to the finding from (Kang et al., 2021; Sarriera et al., 2017; Young & Farber, 2019), the results show that females are more likely to use pooled rides than males; this supports the study from (Shaheen et al., 2021) that reported that females are more likely to pool.

Table 6 shows the results described above and the effect from including random coefficients in the model. Their standard deviations report a significant effect due to heterogeneity in the sample. The coefficient of variation (cv) (the ratio between the standard deviation and the mean), that suggests how big is the variation in the sample, tells us that for example low income (cv = 2.57) is a significantly heterogenous variable. If the random effect was not included, the interpretation may be, for example, that, on average, low-income respondents are more likely to use pooled ridehailing than the high-income group. Instead, the random effect, more specifically, tells us that 65% of the sample follows the average behavior while 35% are less likely to pool. Results show that about 70% of the people 35 – 54 years old are less likely to pool than the younger cohort, while 30% of them are more likely to pool. Similarly, circa 70% of those in the 55 to 64 years old range are less likely to pool than people 34 years old or younger while 30% are interested in pooling. In addition, about 80% of the oldest cohort (65+ years old) is less likely to pool than young people, and circa 20% follow the opposite behavior. Finally, about 70% of those whose trips that are longer are more likely to pool, yet 30% of these trips are likely to follow the opposite behavior

Table 6 Mixed logit model results (n= 5,136)

	Pool vs. Solo ridehailing (reference: solo)	
	Coeff.	*p-value
Age (reference: 18-34 years old)		
35-54	-1.524	***
55-64	-1.704	***
65+	-1.119	.
Household Income (reference: high)		
Low (<$25,000 - $49,999)	0.787	***
Middle ($50,000 - $99,999)	0.533	***
Race (reference: non-white Caucasian)		
White Caucasian	-1.230	***
Gender (reference: Female)		
Male	-0.652	***
N. of travelers for the whole trip (reference: travel alone)		
co-passengers	-1.112	***
Type of payment (reference: rider paid full amount)		
Employer paid for the ride	-2.109	***
Someone else paid 100%	-1.088	***
TNC use frequency (reference: less than 1 per month)		
4+ times a month	0.573	***
1 to 3 times per month	0.469	*
Mobility profile (reference: car)		
Bike	0.657	***
Public transit	0.358	***
Purpose (reference: home)		
Work-School	-0.409	*
Leisure	-0.464	**
Errands	-0.474	*
Change mode (e.g., head to transit hub)	-1.427	***
Trip duration	0.045	***
N. of cars per household	-0.757	***
Population Density (origin) (reference: Non-dense)		
Dense	0.247	.
Random Coefficients		
sd. Intercept	2.345	***
sd. Age 35-54	2.818	***
sd. Age 55-64	-3.318	**
sd. Age 65+	-1.343	
sd. Low income	2.027	***
sd. Middle income	0.942	

	Pool vs. Solo ridehailing (reference: solo)	
	Coeff.	*p-value
sd. Duration	0.077	***
Model results		
Log-Likelihood - Null model	-3352.549	
Log-Likelihood - Final model	-2453.800	
McFadden R^2	0.266	

*****p-value in the table denotes the significance level (‘ ’ not significant, ‘.’ at the 10% level, ‘*’ at the 5% level, ** at the 1% level. ‘***’ below 1% significance level).

8 Conclusions

In the state of California, SB 1014 mandated the development of the Clean Miles Standard and Incentive Program (CMS), with the aim of regulating greenhouse gas (GHG) emissions from TNC fleets. To support the CMS program, the project team at UC Davis carried out three sets of analyses in this study using survey data collected in four California metropolitan regions. The various sections of the project investigated the use of ridehailing among groups with different multimodal travel patterns, the use of pooled ridehailing services, the substitution of ridehailing for other modes of travel and the travel induced by ridehailing.

The results of these research efforts provide evidence that the relationships between ridehailing and the use of other modes at the individual level are nuanced and depend on the individual’s characteristics and travel patterns; however, the project results highlight how ridehailing, on average, tends to often replace more sustainable modes of travel and/or generate new vehicle miles. Furthermore, the research findings include racial, ethnic, and income considerations associated with the substitution of ridehailing for other modes of travel and the use of pooled ridehailing, which motivate policies to address the transportation needs of underserved segments of the California population. The following paragraphs synthesize the results of the three sets of analyses in the project, provide some policy recommendations to support and complement the CMS, and discuss the limitations of the research with proposals for future work.

In the first portion of the study, the project team estimated a weighted, latent class cluster model using week-long GPS-recorded trip logs of 5,053 commuters in four California metropolitan areas: the six-county Sacramento region, the nine-county Bay Area, San Diego County, and parts of Los Angeles and Orange Counties. The latent-class model identified four traveler groups with distinctive forms of modality who tend to adopt certain travel modes over the others: single-occupancy vehicle (SOV) drivers, carpoolers, transit users, and cyclists. A zero-inflated count model distinguished absolute non-users of a given travel mode (i.e., structural zero) from users who happened to not use that mode during the survey period (i.e., sampling zero). Among the four traveler groups, SOV drivers (53% of the total weighted sample) and carpoolers (28%) present more car-oriented and less multimodal mode-use patterns, whereas transit users (15%) and cyclists (4%) report less car-oriented and more multimodal travel patterns. Each traveler group is also shown to have a unique profile with regards to socio-demographics, built-environment attributes, and employers’ subsidies.

To better understand the associations between ridehailing and the use of other travel modes, the project team performed a descriptive statistical analysis of ridehailing use separately for each traveler group described above, including the adoption, frequency, trip attributes, and substitution patterns of ridehailing. Members of the transit user group were found to be most likely to use ridehailing. Since they have the lowest household vehicle ownership, ridehailing offers on-demand automobility, which in turn enables them to access activities and opportunities (Brown, 2019). In fact, transit users are more likely to use ridehailing for mandatory trips (e.g., going to work). They are also more likely to use ridehailing to access/egress other modes (King et al., 2020). Unfortunately, trips in which ridehailing is used to directly connect with transit were found to be rather rare in the project data (only around 3% of all ridehailing trips in the sample were used for this purpose). This finding underscores the need to conduct further data collection efforts to provide insights into the potential complementarity and synergies between ridehailing and public transportation. This potential complementarity provides a compelling rationale for implementing optional credit incentives within the CMS program, which encourage ridehailing companies to actively serve more trips that are used to connect to mass/public transit services. These incentives hold promise in fostering greater integration and efficiency within urban transportation systems.

For each traveler group, their most frequently used mode of travel would often be selected if ridehailing were not available. For example, car users would take car-based modes, while transit users would take transit. Although SOV drivers and carpoolers report substituting ridehailing for vehicle trips most often, they are also found to more likely than the members of the other groups to use premium services which in turn contribute more to congestion (Dhanorkar & Burtch, 2021) and are often offered in less fuel-efficient vehicles than for regular or pooled ridehailing services (Zoepf et al., 2018). In contrast, transit users and cyclists, who often report replacing less-polluting means of travel with ridehailing, may hail rides with less environmental impacts per trip than vehicle-oriented travelers due to pooling behavior.

Further investigating the substitution patterns of ridehailing, the project team also estimated an error components logit model of the choice of an alternative travel option for a trip if ridehailing was not available, using a distinct subsample of 7,333 ridehailing trips by 2,458 survey respondents, excluding the Sacramento region. Among the subsample used to estimate the error components logit model, over 50% of the ridehailing trips replace a transit, active, or carpooling trip, or created new vehicle miles, with transit being the most substituted mode overall (30%). The high transit substitution rate may be partially explained by the concentration of both ridehailing and transit trips in core urban areas in California (Tian et al., 2023). Furthermore, there may be confounding variables pertaining to the competitiveness of alternative modes, such as travel time, that influence the observed sociodemographic effects. For example, Young et al. (2020) found that transit trips are substituted by ridehailing more often when they are of comparable duration. On the other hand, Barajas and Brown (2021) found that origins and destinations of ridehailing trips were most strongly associated with high household income rather than transit supply. While this suggests the importance of socioeconomic variables, the authors also found differing patterns for bus and rail, and that higher transit density predicted more ridehailing trips on weekend nights, which indicates a complex picture. It is recommended that future studies with access to data on the price, level-of-service, and spatiotemporal attributes of alternative travel modes incorporate these variables into their models to control for their potential effects.

Although there is potential to mitigate ridehailing's contribution to congestion by increasing vehicle occupancy rates with pooled services (Li et al., 2019), the results presented in this report indicate that pooled trips are more likely to draw riders away from transit than other travel modes. Taken together, the findings from the analyses presented in sections 5 and 6 of this report indicate that although ridehailing has heterogeneous substitution effects, it tends to replace more sustainable modes of travel and lead to additional vehicle miles traveled (VMT) on average. Therefore, beyond the existing incentive system within the CMS program to award credits for TNC trips that connect to transit, the creation of additional incentives, in particular, for pooled TNC trips that connect to public transit, and the improvement of transit services to be more competitive with pooled ridehailing services are recommended. For example, Schwieterman and Smith (2018) suggest that reducing the number of transfers and the distances people must travel to access transit can improve travel times relative to pooled ridehailing. The fact that respondents without a household vehicle are more likely to replace transit with ridehailing further supports the need for enhanced transit provision in mobility disadvantaged communities. Using ridehailing as a supplement to transit in areas with low transit demand, as suggested by Young et al. (2020), may be a solution worth exploring to improve the mobility of residents while minimizing transit losses, especially if these serve to connect passengers to existing transit stations.

Based on CARB's regulation order, TNC fleets can calculate their average emissions per person miles travel (gCO_2/PMT) based on miles traveled, occupancy and the vehicle's specific CO_2 emissions. The higher the vehicle occupancy, the lower the per-traveler emissions. Pooled ridehailing services, where multiple passengers share the vehicle for all or a portion of the ride, can significantly increase the average vehicle occupancy of TNC trips and thus play an important role in mitigating ridehailing impacts on congestion and GHG emissions (Hou et al., 2020), and may thus help achieve the CMS GHG reduction targets.

Accordingly, the project team estimated a mixed logit model to study the factors that affect the choice between pooled and solo ridehailing, using a subsample of 5,136 ridehailing trips by 1,995 participants in the 2019 TNC Study. Based on the analysis of this sample, pooled rides are popular in dense urban environments; it is therefore suggested that policymakers incentivize TNC providers to offer pooled ridehailing as the default option, e.g., via a fee structure that reduces the price of pooled rides relative to single-occupant rides. The results suggest that frequent TNC users are more likely than other occasional users to consider pooled services. This cohort of TNC users would be among the least affected by the imposition of a proposed single-passenger travel tax, as they already have incorporated pooled on-demand services into their routine and are likely to consider pooled rides in their mode choice decisions on a daily basis. This might be good news for service providers that could even increase their base of users by offering discounts for pooled trips and pooling-to-public transit stations offers.

Another potential way of increasing pooling rates is to capture new customers represented by *those who travel for business*. Employers could adopt pooled ridehailing as the default option for business-related trips, which is currently rarely done, according to the study. As business travel is time-sensitive, and pooled ridehailing is less efficient than solo rides, employers could receive "green" credits for promoting the environmentally friendly but potentially slower pooled ridehailing service. Additionally, "shared-centric" vehicle designs could be developed to provide privacy and onboard productivity, which could offset the longer travel time. Although future research is needed to determine how the trips' payment parameters (i.e., who pays for the trip) interact with the cost of ridehailing trips, these recommendations could encourage the uptake of pooled ridehailing, especially for business travel, while supporting sustainability goals.

Additionally, the research indicates that individuals who prefer *using public transit and active modes* are also more likely to use pooled ridehailing. While there may be some competition and substitution with transit and active modes, this positive attitude towards shared mobility may enhance the potential for mobility-as-a-service to flourish and promote a car-free lifestyle, in which individuals rely on public and shared transportation options. In addition, the research reveals that pooled ridehailing services are most frequently used by *individuals under the age of 35*. While this may be largely due to their stage in life, where they have more time, lower income, and greater willingness to accept longer travel times, it is recommended to explore new public-private partnerships to offer greater financial incentives, adopting more user-friendly and share-centric vehicle designs, and developing educational programs to encourage long-term behavioral change, so that young users continue to opt for pooling as they age.

This might be good news for service providers that could even increase their base of users by offering discounts for pooled trips and pooling-to-public transit stations offers. There is also a sizable opportunity to increase pooling rates by capturing new customers represented by those who travel for business. Employers could introduce pooled ridehailing as the default option when using ridehailing on business, which, according to the study, is currently very seldom used. Since business travel is sensitive to travel time, and pooled ridehailing is less time efficient than the solo alternative, employers could receive a new form of "green" credits in exchange of promoting the more environmentally friendly and delays-prone pooled ridehailing service.

Lastly, it should be acknowledged that the studies presented in this report have several limitations. First, as a cross-sectional analysis, the study on the multimodal travel patterns of California residents does not claim causality from travel modality to the adoption or frequency of ridehailing (or vice versa). To determine causality, there is a need to develop longitudinal research designs, with which one may examine whether changes in modality lead to greater or lesser adoption of ridehailing (or vice versa), which would be a relevant direction for future research endeavors. Second, the dataset used in the present research lacks attitudinal information on various aspects such as travel modes, built-environment attributes, active lifestyles, adoption of ICT, and environmentalism, which previous studies have shown to have a significant role in explaining travel behavior choices. GPS-tracking data such as those used in this study should be combined with rich questionnaires to objectively capture travel patterns and incorporate psychometrically rich individuals' characteristics.

Finally, it should be noted that the project is based on the analysis of data collected before the COVID-19 pandemic. Therefore, it refers to travel behavior choices and service conditions that were present in those years, which might not be entirely applicable to the modified post-pandemic conditions of the transportation sector. Additional research would be recommended to evaluate how these relationships might have evolved in recent years.

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