Transportation Research Part A 148 (2021) 199–222

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

To Pool or Not to Pool? Understanding opportunities, challenges, and equity considerations to expanding the market for pooling

Jessica R. Lazarus [a,b,c], Juan D. Caicedo [a,c], Alexandre M. Bayen [c,d], Susan A. Shaheen [a,b,c]

[a] *Department of Civil and Environmental Engineering, University of California, Berkeley*
[b] *Transportation Sustainability Research Center, University of California, Berkeley*
[c] *Institute Transportation Studies, University of California, Berkeley*
[d] *Department of Electrical Engineering and Computer Science, University of California, Berkeley, United States*

ARTICLE INFO

Keywords:
Ridesharing
Pooling
Transportation Network Company (TNC)
Ridesourcing
Ridehailing
Mode Choice Modeling
Travel Demand Management

ABSTRACT

On-demand mobility services such as bikesharing, scooter sharing, and transportation network companies (TNCs, also known as ridesourcing and ridehailing) are changing the way that people travel by providing dynamic, on-demand mobility that can supplement public transit and personal-vehicle use. Adoption of on-demand mobility has soared across the United States and abroad, driven by the flexibility and affordability that these services offer, particularly in urban areas where population density and land use patterns facilitate a reliable balance of supply and demand. The growth of app-based ridesharing, microtransit, and TNCs presents a unique opportunity to reduce congestion, energy use, and emissions through reduced personal vehicle ownership and increased vehicle occupancy, the latter of which is largely dependent on the decisions of individual travelers to pool or not to pool. This research provides key insights into the policy levers that could be employed to reduce vehicle miles traveled and emissions by incentivizing the use of pooled on-demand ride services and public transit. We employ a general population stated preference survey of four California metropolitan regions (Los Angeles, Sacramento, San Diego, and the San Francisco Bay Area) to examine the opportunities and challenges for drastically expanding the market for pooling, taking into account the nuances in emergent travel behavior and demand sensitivity across on-demand mobility options. Although *high-frequency TNC users* – those that use TNCs once a week or more - are more likely to consider pooling than less frequent users and reflect more multimodal travel behavior than other travelers, we find that the most captive and price sensitive TNC users are often the most vulnerable. *Heavy TNC users* – those using TNCs more than three days per week - are disproportionately low income, more likely not to own or lease a car and more likely to use TNCs for essential trip purposes than are less frequent users. Pooling demand sensitivity varies significantly across trip contexts, metropolitan regions, socio-demographics, travel behavior, and attitudes and perceptions toward sharing. We estimate the time and price tradeoffs in choosing between ride alone and shared on-demand service options, finding significant differences across values that travelers place on each component of travel time (wait time, access/egress walking time, and in-vehicle time) by geography and income level. We discuss the potential to leverage these insights to develop policies that combine pricing, curb management, and promotional strategies to increase the pooling market share.

E-mail address: jlaz@berkeley.edu (J.R. Lazarus).

https://doi.org/10.1016/j.tra.2020.10.007
Received 30 October 2019; Received in revised form 6 April 2020; Accepted 11 October 2020
0965-8564/

1. Introduction

In recent years, the transportation ecosystem in most urban areas across the globe has swelled to include a suite of technology-enabled, shared mobility services such as carsharing, bikesharing, scooter sharing, and transportation network companies (TNCs, also known as ridesourcing and ridehailing). These innovative services are changing the way that people travel by providing dynamic, on-demand mobility that can supplement public transit and personal-vehicle use. However, the broader impacts of innovative mobility services are highly uncertain and largely dependent on the ubiquity of riders willing to share their rides, particularly when using TNCs such as Lyft and Uber. There is growing evidence that TNCs are contributing large sums of additional vehicle miles traveled (VMT) in large dense metropolitan areas of the United States (U.S.) (Schaller, 2017; SFCTA, 2017; Schaller, 2018), with an estimated 20% to 45% of TNC VMT consisting of "deadheading" miles—miles driven without a passenger in the vehicle (Henao and Marshall, 2018; Cramer and Krueger, 2016; SFCTA, 2017; Schaller, 2017). Pooling rides can increase the average vehicle occupancy of TNC trips and thus reduce VMT, energy use, and GHG emissions (Viegas et al., 2016; WEF and BCG, 2018; Greenblatt and Saxena, 2015). Yet, there is limited understanding of the sensitivity for pooling demand, particularly within the context of on-demand ride services. Knowledge of individual travel behavior and decision-making processes for choosing between the growing number of on-demand mobility services is critical for devising equitable and effective incentive mechanisms for increasing vehicle occupancy while maintaining the affordability and mobility provided by such services.

Carpooling, or ridesharing, is the grouping of multiple travelers into a car or van to complete a common trip. Carpooling has a long history as a TDM tool in North America, with large employers historically playing a central role in the incentivization and facilitation of commuter carpooling programs. In addition, casual carpooling has thrived for decades in the metropolitan regions of Houston, Texas, Washington, D.C. and Northern Virginia, and the San Francisco Bay Area, where access to High Occupancy Vehicle (HOV) lanes has maintained an active community of carpoolers that meet up at established public pickup and dropoff locations to save time and money commuting to and from central employment centers (Shaheen and Cohen, 2019). Recently, socio-economic forces coupled with technological innovation have given rise to a new wave of pooling enabled by app-based services that reserve, match, and process payments for rides on-demand. Several mobility companies have launched app-based ridesharing services (e.g., Waze Carpool, Scoop), although some pilots have been discontinued due to low match rates (e.g., Lyft Carpool) (Shaheen and Cohen, 2019).

TNCs offer pooled on-demand ride options (e.g., uberPOOL and Lyft Shared Rides) in which users may choose to share a ride with another passenger traveling along a similar path for a reduced fare. In 2017, just 20% and 40% of all Uber and Lyft rides, respectively, were pooled rides (Shaheen and Cohen, 2019). In New York City, where data on matching rates are available, only about 22% to 23% of requested Lyft Line (now Lyft Shared rides) and uberPOOL (now UberPool) rides in 2018, respectively, resulted in matched trips (Schaller, 2018). In 2017, both major TNC companies launched modified versions of their pooled on-demand ride services, called Uber Express POOL and Lyft Shared Ride Saver, which require that passengers walk a short distance to/from their pickup/dropoff location (Lyft, 2017; Uber, 2017). These services resemble microtransit services, which offer flexible- or fixed-route rides with fixed-schedule or on-demand service in shuttles or vans (Shaheen and Cohen, 2019).

Several strategies to mitigate the negative impacts of TNC use have emerged across North America at both the state and local levels. These include vehicle and driver licensing and registration fees, access fees and restrictions to specific pickup or dropoff locations (e.g., airports, stadiums, etc.) or areas (e.g., downtown zones) and pricing policies that apply a flat, percentage-based, or per-mile surcharge to TNC trips within a jurisdiction. In some cases, discounts are provided for pooled TNC trips. Examples include the: 1) New York State Congestion Surcharge, which applies a $2.75 fee to all ride-alone TNC trips and $0.75 to all pooled TNC trips that start, end, or pass through Manhattan south of 96th Street; 2) San Francisco Rideshare Tax, which applies a 3.25% and 1.5% surcharge to all ride-alone and pooled TNC trips, respectively, that start in San Francisco; and 3) City of Chicago congestion pricing, which applies a $3 and $1.25 surcharge to all ride-alone and pooled TNC trips, respectively, that start or end in a designated downtown zone during weekday peak hours (between 6 AM and 10PM) and applies a $1.25 and $0.65 surcharge on all other ride-alone and pooled TNC trips, respectively. The disposition of funds from state and local TNC taxes and fees includes general funds to congestion mitigation funds and even public school funds.

Although there is a growing literature focused on characterizing the socio-demographics, travel behavior, and mode shifts of TNC users, there remains a limited understanding of the differentiation between pooled and ride-alone TNC demand. It is not clear whether the enacted strategies provide efficient disincentives to curb TNC use nor whether the established discounts are sufficient to incentivize pooling. Moreover, it remains to be seen whether the effects of pricing policies are distributed equitably across the population. It is imperative to develop a deeper understanding of which population segments are most likely to be affected by pricing policies as well as the magnitude of VMT and emission reductions that may be achieved by various strategies.

This article investigates the opportunities and challenges for expanding the market for pooling by incentivizing TNC users to pool. Using a stated preference survey of the general population in four California metropolitan regions (Los Angeles, Sacramento, San Diego, and the San Francisco Bay Area) in 2018, we examine the nuances in travel behavior and demand sensitivity across on-demand and pooled ride options. *High-frequency TNC users*—those that use TNCs at least once a week—pose a notable opportunity, as they are more likely to consider pooling and reflect more multimodal travel behavior than other travelers. However, we observe that the most captive and price sensitive TNC users are often the most vulnerable: *heavy TNC users*—those using TNCs more than three days per week—are disproportionately low income, more likely not to own or lease a car, and more likely to use TNCs for essential trip purposes than are less frequent users. A discrete choice analysis of stated preferences across ride alone, door-to-door shared (e.g., Lyft Shared rides, UberPool), and indirect shared (e.g., Uber Express POOL, Lyft Shared Saver) rides reveals that females, travelers aged 18 to 30 years old, travelers with an annual income less than $35,000, car owners/leasers, and public transit users are among the most likely to share an on-demand ride. However, likelihood to share varies significantly by the origin, destination, and time sensitivity of a trip. The relative demand sensitivity to estimated wait times, in-vehicle times, and walking access/egress times reveals significant opportunities to shift deadheading and passenger vehicle miles to walking miles by incentivizing indirect shared rides. In addition to direct price incentives and indirect operational incentives that reduce wait times and in-vehicle times, we quantify the impact that promotional offers can have on a traveler's choice to pool or not to pool.

The remainder of this article is organized into five key sections. First, the authors present literature and prior research on pooling. The survey design and methodology for discrete choice analysis are presented next, followed by a presentation of results. Finally, the authors discuss the broader implications of the study and provide policy recommendations and conclusions.

2. Background

Pooling—the shared use of a vehicle for multiple passengers to complete journeys of similar origin and destination—exists in numerous forms today. From traditional ridesharing (e.g., carpooling and vanpooling) to on-demand ride services such as microtransit, taxi sharing, and shared ride TNC services, pooling offers travelers a cheaper alternative to private-vehicle use that generates important societal and environmental benefits through the reduction of VMT and GHG emissions. In this section, we provide an overview of the state of the knowledge of different forms of pooling.

3. Traditional ridesharing (carpooling and vanpooling)

Traditional ridesharing includes acquaintance-based and organization-based carpools (groups of two to six traveling together in a car) and vanpools (groups of seven to 15 commuting together in one van) as well as casual carpooling, also known as "slugging" (Shaheen and Cohen, 2019). Ridesharing can be recognized by many names, including liftsharing or car sharing in the UK, and carpooling or vanpooling in North America. However, it differs from for-hire vehicle services such as taxis, jitneys, and TNC services in that ridesharing payments, when collected, are not intended to result in financial gain and typically only partially cover the driver's cost (Chan and Shaheen, 2011). In addition, ridesharing drivers share a common origin and/or destination with their passengers.

Ridesharing has a long history as a transportation demand management (TDM) tool in North America. It first emerged in the U.S. during World War II as a result of a 1942 federal regulation that sought to conserve rubber for the war effort (Chan and Shaheen, 2011). Carpooling and eventually, vanpooling, have since continued to have a role in congestion and parking supply management, particularly at large employment sites and during periods of economic stress. HOV and High Occupancy Toll (HOT) lanes have historically encouraged the adoption of ridesharing in regions where they provide significant time and cost savings (Shirgaokar and Deakin, 2005; Neoh et al., 2017). The phenomenon of casual carpooling, or slugging, began in the 1970s and has maintained prominence in the regions of Houston, Texas, Washington, D.C. and Northern Virginia, and the San Francisco Bay Area, where participation is driven by significant driver and passenger travel-time savings from gaining access to HOV lanes, as well as passenger cost savings and perceived convenience over driving alone or taking other alternative transportation modes (Shaheen and Cohen, 2019).

While individual likelihood to carpool has been found to increase for lower income groups, younger age groups, and minority groups (typically Hispanics and African Americans), these factors are all highly correlated with a lack of car ownership, the strongest internal predictor of carpooling (Correia and Viegas, 2011; Neoh et al., 2017, Shaheen and Cohen, 2019). Attitudinal factors, such as perceptions of the convenience and reliability of ridesharing, coupled with situational factors influencing the: 1) quality of public transit alternatives to driving, 2) flexibility of work schedules, and 3) availability of workplace incentives have a stronger positive influence on the propensity to rideshare than do socio-demographic factors (Neoh et al., 2017; Vanoutrive et al., 2012; Koppelman et al., 1993). In the San Francisco Bay Area and Washington, D.C., casual carpooling is most heavily used during the morning commute, as many passengers opt to use public transit for their commute home when there is generally more travel-time flexibility (Shaheen and Cohen, 2019).

The commute mode share of ridesharing in the U.S. has declined over the past decade, from 10.4% in 2007 to 8.9% in 2017 (U.S. Census Bureau, 2018a). In California, the commute mode share of ridesharing has declined as well, from 11.9% in 2007 to 10% in 2017. The nation's most populous metropolitan regions have also experienced declines in ridesharing commute mode share, although many saw a lower rate of decline than the national average, particularly between 2015 and 2017. Although a new era of smartphone enabled ridesharing emerged in North America during this period, it is yet to be determined whether this has had an impact on ridesharing rates. Several mobility companies have launched app-based ridesharing services including: Waze Carpool, Scoop, Carzac, and Ride (Shaheen and Cohen, 2019). In March 2016, Lyft piloted a traditional ridesharing service in partnership with the Metropolitan Transportation Commission in the San Francisco Bay Area. The pilot was discontinued after six months due to low match rates (Shaheen and Cohen, 2019).

3.1. Pooled on-demand ride services

On-demand ride services provide for-hire rides to travelers through smartphone applications that facilitate reservations, driver dispatching, and payment. They include TNC services, which offer both ride-alone (e.g., uberX, Lyft Classic) and pooled ride options (e.g., uberPOOL, Lyft Shared Rides), also known as ridesplitting. Ridesplitting also encompasses taxi sharing services, which enable multiple unacquainted users with similar routes to split the fare of a shared ride in a taxi (Shaheen and Cohen, 2019). Lastly, on-demand transit services, called microtransit, frequently provide rides in a van or bus with flexible service in terms of pickup and dropoff times and/or locations.

Pooled TNC services are typically provided within the same smartphone app-based user interface as ride-alone TNC options, allowing passengers to choose to share their ride with a stranger traveling along a similar path. TNC users are usually quoted a discounted price and a longer estimated total travel time for a pooled ride compared to the ride-alone option. When Lyft and Uber first launched in 2012 and 2013, respectively, only private on-demand ride services were offered (Shaheen and Cohen, 2019). Both TNCs introduced shared-ride services in August 2014, originally called uberPOOL and Lyft Line (now called Lyft Shared Rides). As of December 2017, 20% and 40% of all Uber and Lyft rides, respectively, were pooled rides (Shaheen and Cohen, 2019). In 2017, both TNC companies started piloting modified versions of their pooled on-demand ride services, called Uber Express POOL and Lyft Shared Saver, which require that passengers walk a short distance to/from their pickup/dropoff location (Lyft, 2017; Uber, 2017). This newest iteration of pooled on-demand ride services resemble microtransit services, which offer flexible- or fixed-route rides with fixed-schedule or on-demand service in shuttles or vans (Shaheen and Cohen, 2019).

3.2. Microtransit

The recent growth in microtransit service is in part a renewal of the core pooled service provided by jitneys that have offered rail feeder, circulator, and high-frequency areawide service in metropolitan regions such as: the San Francisco Bay Area, San Diego, Atlantic City, and Miami (Cervero, 1997). Chariot, which launched in San Francisco in 2014 offered rides in 14-person passenger vans along fixed routes that were ‘crowdsourced’ by users in Austin, Columbus, London, New York City, San Antonio, San Francisco, and Seattle (Shaheen and Cohen, 2019). Another microtransit service called Bridj emerged in 2014, which promised on-demand, flexibly routed service similar to the indirect pooled rides offered by Uber Express POOL and Lyft Shared Ride Saver, through 14-seater passenger vans. A study during six-months of a pilot of Bridj in Kansas City found that the majority of riders used the service to commute and for work-related travel, with price affordability and convenience being the key motivating factors for use (Shaheen et al., 2016). While both Bridj and Chariot ended their operations in 2017 and 2019, respectively, a third prominent microtransit service called Via operates in Arlington (Texas), Chicago, London, New York City, Washington D.C., West Sacramento, and Los Angeles (Shaheen and Cohen, 2019).

3.3. Early understanding of pooled on-demand ride services

Overall, TNC users tend to be younger and more highly educated than the general population (Circella et al., 2018; Henao and Marshall, 2018; Smith, 2016; Clewlow and Mishra, 2017; Gehrke et al., 2018; Rayle et al., 2016; Schaller, 2018). Findings on the income and racial/ethnic distributions of TNC users have been mixed, with some studies suggesting that TNC users have higher incomes (Clewlow and Mishra 2017; Schaller, 2018) and are more likely to be white/Caucasian (Hampshire et al., 2017; Henao and Marshall, 2018), while others have found that these distributions of TNC users are closely aligned with those of the general population in the study area (Rayle et al., 2016; Feigon and Murphy 2018; Gehrke et al. 2018). Brown (2018) found that, on average, Lyft users living in low-income neighborhoods in Los Angeles County make more trips per capita, and they are more likely to pool than those living in neighborhoods with a higher median income.[1] This study also found that users living in majority-black and majority-white neighborhoods of Los Angeles County take more trips and are less likely to pool than those living in more diverse neighborhoods.

TNC services have been found to contribute large sums of additional VMT in large dense metropolitan areas of the U.S. (Schaller, 2017; SFCTA, 2017; Schaller, 2018). The total VMT produced by TNCs includes the miles driven by drivers en-route to their market of choice, as well as those driven while roaming and unreserved, driving to pickup a passenger, and driving with a passenger in tow. The former three phases of service represent ‘deadheading’ or miles driven without a passenger in the vehicle. Studies estimating the percent of VMT caused by deadheading typically focus on miles driven while awaiting a ride request and driving to the passenger pickup point. These studies have estimated that 20% to 45% of miles driven by TNC vehicles are accounted for by deadheading (Henao and Marshall, 2018; Cramer and Krueger, 2016; SFCTA, 2017; Schaller, 2017; CARB, 2019).

To the authors’ knowledge, there are six studies of TNC services that measure vehicle occupancies, five of which explicitly consider pooled-ride services. An intercept survey of TNC users in the San Francisco Bay Area prior to the launch of pooled rides found that half of ride-alone TNC trips had more than one passenger, with an average occupancy of 2.1 passengers per trip (Rayle et al., 2016). Intercept surveys conducted in Denver, Colorado during Fall 2016 and Boston, Massachusetts during Fall 2017 observed average occupancies of 1.36 and 1.52 passengers per trip, respectively (Henao and Marshall, 2018; Gehrke et al., 2018). The Boston study found that pooled rides comprised about a fifth of trips surveyed, while in the Denver study, about 13% of all rides were requested as pooled services, about 85% of which were not matched with another rider. A survey distributed across California in 2018 found that the average occupancy of respondents’ most recent trips was about 1.9 passengers per trip, with lower occupancy observed on weekends and greater occupancy observed during nighttime trips (Circella et al., 2019). The California Air Resources Board analyzed records from trip diaries collected from 31 TNC drivers in Spring 2019, finding time-weighted occupancies of 1.57 and 1.54 for pooled and non-pooled rides, respectively. About 15% and 12% of trips from the 2018 and 2019 California studies, respectively, were pooled trips. Finally, using a dataset of all Lyft trips that occurred in Los Angeles County from September to November 2016, Brown (2018) found that Lyft Line was used for 29.2% of all Lyft trips and 32% of all peak-hour trips during that period.

As with traditional ridesharing, a critical mass of ridership is necessary to facilitate efficiency gains from pooled on-demand ride services. Based on data from TNC trips in New York City in February 2018, only about 22% to 23% of requested Lyft Line and

[1] Due to data limitations, the findings by Brown (2018) are based on the census tract median household income corresponding to the zip code of residence for the rider of each trip.

uberPOOL rides, respectively actually resulted in a matched trip (Schaller, 2018). In contrast, about 60% of Via trips in New York City are shared (Schaller, 2018). Simulation-based studies focused on shared automated vehicle (SAV) fleets have projected the impacts of on-demand pooling, finding that the potential of SAVs to reduce VMT is highly dependent on the percent of trips that are shared and the rate of replacement of single occupant trips by pooled trips (Viegas et al., 2016; WEF and BCG, 2018; Greenblatt and Shaheen, 2015; Greenblatt and Saxena, 2015).

4. Methodological approach

This study analyzes data from a general population stated preference (SP) online survey of residents from four CA metropolitan regions conducted from August to December 2018: Los Angeles, Sacramento, San Diego, and the San Francisco Bay Area. The survey design and analysis are informed by a large body of literature on travel demand modeling (Ben-Akiva and Lerman, 1985: Train, 2009), particularly for estimation of the value of time (VOT) and a traveler's willingness to pay for travel time reductions (Brownstone and Small, 2005; Wardman, et al., 2016; Zamparini and Reggiani, 2007). The estimation of a discrete choice model for the choice of TNC ride options enables the investigation of the significant factors influencing a TNC user's choice to pool or not to pool, as well as the explicit estimation of a traveler's VOT across different time segments of a TNC trip. VOT is calculated as the ratio of the sensitivity of demand to a particular travel time component (e.g., walking time to/from a pickup/dropoff location, waiting time, in-vehicle time) to the sensitivity of demand to travel cost. The VOT for driving has been found to vary from about 50% to 100% of the mean hourly wage for the population of interest (Brownstone and Small, 2005; Wardman et al., 2016; Zamparini and Reggiani, 2007; United States Department of Transportation (USDOT), 2016). While historical VOT waiting time estimates for public transit have varied from about 1.5 to 2 times the VOT for in-vehicle time, a recent SP survey of Dutch citizens regarding pooled on-demand ride services similar to microtransit found that the waiting time VOT was about 1 to 1.5 times the VOT for in-vehicle time (Alonso-Gonzalez, et al., 2020). While this SP survey stipulated a constant one minute walk time estimate, our study includes walking time as an additional travel time component. In addition, we explore the regional variation in travel behavior and demand sensitivity for on-demand rides across four California metropolitan regions. This section details the methods used for data collection, survey analysis, and discrete choice analysis.

4.1. Survey design

The online survey included multiple-choice questions regarding respondents' socio-demographic characteristics, travel profiles, typical TNC use, attitudes and perceptions toward TNCs and pooling, and a series of four to five stated preference mode-choice experiments.

Respondents were asked to indicate their familiarity with TNC services such as Lyft and Uber. Respondents who had never used TNCs were presented with a brief explanation of such ride services. All respondents were then presented with instructions explaining that the following set of questions would present hypothetical travel scenarios in which the respondent would be asked to choose a transportation option based on the information provided. Respondents were asked to imagine that they were traveling alone and could choose from the following options, as presented:

- **Ride-alone TNC:** a service such as uberX/ Lyft Classic where you request a direct, door-to-door ride for yourself.
- **Door-to-door shared ride:** a service such as uberPOOL/ Lyft Shared Rides (formerly Lyft Line) where you request a door-to-door ride for yourself and your route may deviate to pickup or dropoff one to three additional passengers riding along a similar route.
- **Indirect shared ride:** a service such as Uber Express POOL that is identical to a door-to-door shared ride, except you are assigned pickup and dropoff locations that may require you to walk several minutes to and from the origin and destination locations you designate in the ride request. Indirect shared rides may have one to five additional passengers.

In each of the first four scenarios, respondents were asked to imagine that they were making a trip with a specified context provided by the trip origin, destination, and a time constraint. The trip purpose was indicated by the destination, which was selected randomly from the following possibilities: home; a restaurant/bar; an event (e.g., sports event, theater, concert); the airport; a recreational/social activity (e.g., a park, the beach, etc.); or a public transit station. Further context regarding the location in which the hypothetical mode choice occurred was randomly generated to be either 'from home' or 'from somewhere other than home.' Finally, the time constraint was randomly generated to provide the context that the trip would be made with plenty, some, or no time to spare. Respondents that self-identified as being employed (either full- or part-time) or a student were presented with a fifth scenario in which they were asked to consider that they were planning a commute trip to work (or school). In the commute scenario, the time constraint variable was not presented and the trip origin and destination were home and work/school, respectively.

As shown in Fig. 1 below, the alternative-specific attributes for each transportation option were presented in a table format including: 1) estimated wait time, 2) estimated walking time to or from the pickup or dropoff locations, 3) estimated in-vehicle time, 4) estimated total time, 5) estimated cost, and 6) expected range of additional passengers. Only the indirect shared-ride option included the estimated walking access/egress time attribute, as the other two ride options provide door-to-door service. As with a typical shared TNC ride quote, respondents were not given an estimate of the exact number of additional passengers that may join the ride. The indirect shared ride was specified to include up to five additional passengers to account for a ride experience similar to dynamic microtransit in which a larger vehicle such as a van or shuttle may be used for this service type, whereas the door-to-door shared ride was specified to include up to three additional passengers to differentiate it as a trip that would typically be served by a smaller vehicle such as a sedan.

Imagine you are making a trip **from somewhere other than home** to **a restaurant/bar** with **some time to spare.**

Please carefully review the transportation options available to you for this trip.

	Ride Alone	Door-to-Door Shared Ride	Indirect Shared Ride
Estimated wait time	9 minutes	6 minutes	2 minutes
Estimated walking time to/from pickup/dropoff	-	-	7 minutes
Estimated in-vehicle time	28 minutes	48 minutes	48 minutes
Total estimated time	37 minutes	54 minutes	57 minutes
Estimated total cost	$18	$11.7	$9.6
Additional passengers	0	1 to 3	1 to 5

Which of these choices would you prefer for a trip from somewhere other than home to a restaurant/bar with some time to spare?

Ride Alone

Door-to-Door Shared Ride

Indirect Shared Ride

a) A SP experiment without promotions

Now, consider that you have the following options **for the same trip (traveling from somewhere other than home** to **a restaurant/bar** with **some time to spare)**.

Please carefully review the transportation options available to you for this trip.

	Ride Alone (TNC/Ridesourcing)	Personal Vehicle	Public Bus (e.g., MTS buses)	Rail (e.g., San Diego Trolley)
Estimated wait time	9 minutes	-	6 minutes	14 minutes
Estimated walking time to/from pickup/dropoff	-	-	7 minutes	2 minutes
Estimated in-vehicle time	28 minutes	28 minutes	35 minutes	1 hour 8 minutes
Total estimated time	37 minutes	28 minutes	48 minutes	1 hour 24 minutes
Estimated total cost	$18	$5 (parking and tolls)	$9	$2.5

Which of these choices would you prefer for a trip from somewhere other than home to a restaurant/bar with some time to spare?

Ride Alone (TNC/Ridesourcing)

Personal Vehicle

Public Bus

Rail

b) A SP experiment with promotions

Fig. 1. Example Stated Preference Experiments.

All other alternative-specific attributes were generated randomly from pre-specified distributions of discrete values that were purposefully chosen to cover a range of possible scenarios.[2] The estimated wait times for each shared-ride option and the estimated walking time for indirect shared rides were independently and randomly generated. The estimated in-vehicle times and costs of each alternative were generated in a cascading fashion, starting with the random generation of the estimated in-vehicle time for the ride-alone TNC option, which was assumed to travel the most direct path among all options. The range of possible values of the estimated in-vehicle times for door-to-door shared rides were specified to be greater than or equal to that of the ride-alone option to allow for the possibility that the rider is at best the last to be picked up and first to be dropped off in the shared ride. For the indirect shared ride, the range of possible in-vehicle times also included values that were slightly faster than the ride-alone option to reflect the potential efficiency gains from dispatching rides for passengers that do not have to be directly picked up or dropped off from their requested origin and destination. In order to constrain the scope of the experiments to trip distances for which most people would not choose to walk or bike, the minimum estimated in-vehicle time across all scenarios and transportation options was seven minutes.

The estimated total cost for the travel options were also chosen based on the estimated in-vehicle time of the ride-alone TNC option to reflect the time- and distance-based pricing of TNC services (Uber, 2018; Lyft, 2018). The range of cost estimates was amplified to test the sensitivity of respondents to prices that may be cheaper or more expensive than contemporary TNC pricing. In doing so, the SP experiment design and resulting discrete choice analysis enables consideration of policy scenarios in which the proliferation of SAV ride services have drastically reduced the prices of on-demand rides, as well as scenarios in which pricing policies are enacted to increase the prices of certain on-demand services. The estimated costs for the door-to-door shared TNC were randomly generated from values ranging from 90% to 65% of the ride-alone cost. The estimated cost for the indirect shared TNC was then randomly generated from values ranging from 90% to 65% of the door-to-door shared TNC cost.

In the third and fourth scenarios, a promotional offer was included as an additional alternative-specific attribute for the shared TNC

[2] The distributions of the time and cost attribute levels are presented in Table A1. All other attribute levels were generated using a uniform distribution.

options, as demonstrated by the example in Fig. 1b above. Three types of promotions were tested, one of which would only appear if the randomly generated trip destination was ‘to a public transit station,’ while the other two were eligible to appear for any trip purpose. The public transit-focused promotion stated: ‘Take a door-to-door (indirect) shared ride to public transit and get $2 (or $5 or $7) off your transit fare,’ where the public transit discount offered was randomly generated from those three values. The second promotional type offered: ‘Take 2 (5, 7, or 10) door-to-door (indirect) shared rides and get one door-to-door (indirect) shared ride free.’ Finally, the third promotion offered: ‘Take one door-to-door (indirect) shared ride and get 5% (7%, 10%, 12%, 15%, or 20%) off your next door-to-door (indirect) shared ride.’ The promotional values for each of the two latter offers were also randomly generated from the values listed.

4.2. Survey analysis

In total, 2,538 respondents completed the survey. A number of response quality checks were applied to filter out incomplete responses, resulting in a final sample size of 2,434. The survey results were analyzed for the purposes of understanding the socio-demographic and travel profiles of California residents that use TNC services, the nature of TNC use, and the extent to which TNC users share rides. Furthermore, the analysis focused on characterizing high frequency TNC users to provide insights into which population segments represent the most captive demand for TNCs and other on-demand ride services, including app-based carpooling and future SAV services. When applicable, analysis of the responses from TNC users and nonusers are provided.

The primary test of significance used in the analysis is the two-proportions z-test in which the null hypothesis is that the two distributions are equal. Unless otherwise noted, all results that are stated to be ‘significant’ have failed the null hypothesis of the two-proportions z-test at a 99% significance level.

4.3. Discrete choice analysis

In order to investigate the significant factors in an individual’s choice to pool when using TNC services, a discrete choice analysis (DCA) was performed using the SP survey data. DCA is a method used to model the choice from an exhaustive, finite set of mutually exclusive alternatives, based on the principles of utility maximization (Ben-Akiva and Lerman, 1985; Train, 2009). The objective is to estimate a parameterized random utility model for each of the alternatives, composed of a deterministic and a random component. As defined in Equation (1), the utility of alternative j to individual n, denoted as U_{nj}, is the sum of the linear combination of observable independent variables, X_{nj}, multiplied by corresponding coefficients, β_{nj} (the deterministic component), plus an error term representing unknown factors, ε_{nj} (the random component).

Equation (1). A Random Utility Model

$$U_{nj} = \beta_{nj} X_{nj} + \varepsilon_{nj} \tag{1}$$

The probability that a particular individual chooses any one of the alternatives, defined by the logit model in Equation (2), is the probability that the chosen alternative provides that individual with the greatest utility across all available alternatives. In the multinomial logit model, the scale parameter μ is conveniently constrained to a value of one, following the assumption that the variances of the error terms are homoscedastic (Ben-Akiva and Lerman, 1985). More refined models, such as the nested multinomial logit, relax this assumption by allowing different scale parameters across alternatives. The maximum likelihood approach for estimating the parameters is used (Ben-Akiva and Lerman, 1985).

Equation (2). The Probability That Decision Maker n Chooses Alternative j

$$P_{nj} = Prob\left(U_{nj} > \max_{i \in C_n, i \neq j} (U_{ni})\right) = \frac{e^{\mu \beta_{nj} X_{nj}}}{\sum_{i \in C_n} e^{\mu \beta_{ni} X_{ni}}} \tag{2}$$

A total sample of 10,912 SP choice experiments from 2,398 individual respondents was included in the DCA to produce a TNC mode choice model that predicts the preferred ride option of a particular traveler in a given trip context. Responses to multiple SP choice experiments from each respondent are included as independent observations in the model.

4.4. Model estimation

The TNC choice model is a multinomial logit model estimated from the responses to the SP choice experiments, in which respondents indicated which one of three TNC-ride options they preferred given the trip context and attributes of each alternative. The model was specified using a backward elimination procedure. Table 1 below provides the full list of variables considered as candidate model parameters. All trip context and alternative-specific attributes were included in the candidate parameter set. An additional set of individual characteristics, including socio-demographic, travel profile, and attitudinal variables were chosen as candidates for the model based on the survey analysis. Ordinal variables (e.g., education and all attitudinal variables) were treated as continuous variables for model simplicity.

In addition, a nested multinomial logit specification was estimated to test for correlation between the shared-ride options. The estimated nest-scale parameter failed the null hypothesis test of being equal to one with a 90% confidence level. Moreover, the model was rejected by the likelihood ratio test comparing it to the multinomial logit specification with a 90% confidence level.

With the exception of the estimated cost parameter, all parameters were initially specified as alternative-specific, with the ride-

Table 1
Candidate Parameters for DCA.

Contextual Variables	Alternative-Specific Attributes	Individual Characteristics
Origin	Estimated wait time	Metropolitan region
Destination (trip purpose)	Estimated in-vehicle time	Gender
Time sensitivity	Estimated walking time	Age
	Estimated cost	Education
	Promotion: % off next shared ride	Racial/Ethnic group
	Promotion: number of shared rides to get one free	Employment
		Income
	Promotion: $ off of public transit fare	Medical condition/handicap
		Car ownership
		TNC tenure (years since started using)
		TNC trip frequency
		Drive-alone trip frequency
		Public bus trip frequency
		Rail trip frequency
		Carpool/Vanpool trip frequency
		Taxi trip frequency
		Shared micromobility trip frequency
		Comfortable being driven
		Comfortable sharing rides
		Enjoy chatting with driver
		Enjoy chatting with passengers
		Believe shared rides are more environmentally friendly than ride-alone TNCs

alone TNC option as the base. In other words, the initial model specification included separate coefficients for the door-to-door shared rides and indirect shared rides for each alternative-specific parameter. The first step in the backward elimination involved consolidating parameters using the likelihood ratio test to determine if a significant[3] improvement in the goodness-of-fit of the model could be achieved by restricting each parameter from two alternative-specific parameters (one for each shared-ride option) to one generic parameter for both shared-ride options. First, the parameters for which the confidence intervals of the unrestricted parameters overlapped were tested for consolidation, which was followed by the remainder of the parameters in order of decreasing p-value. As a result, only parameters with a significant difference in their relationship to the likelihood that an individual chooses one shared-ride option over another remained as two separate model parameters. In the next step of the backward elimination, parameters were tested for removal from the model specification (in order of decreasing p-value), again using the likelihood ratio test for improvement in goodness-of-fit with a significance level of 95%.

Next, variables were tested for their correlation to the metropolitan region of the decisionmaker's residence. Naturally, each metropolitan region surveyed has unique cultural, land use, and geographic characteristics that can influence the significance of various factors in an individual's transportation mode choices. While specification of four separate region-specific models was an undesirable final outcome of the DCA due to the necessary sacrifice in predictive power from reduced sample sizes, four such models were estimated as an intermediary step in the model specification process to identify parameters that could improve the core model by being specified for each metropolitan region. Parameters for which the confidence intervals of the estimated coefficients overlapped across multiple region-specific models were then interacted in the full model and tested using the likelihood ratio test with a significance level of 95%. Following this process, the resulting region-specific parameters were tested once more on the basis of improvement in goodness-of-fit from either the generic or alternative-specific specification. For example, although the final model estimation suggests a significant difference in the relationships between the utility of door-to-door shared rides and indirect shared rides for weekly TNC users in the San Francisco Bay Area, there is no such difference in utilities across the two shared ride options for weekly TNC users in the remaining three metropolitan regions. Finally, the same process was undertaken for socio-demographic variables to check for the significance of additional interactions.

4.5. Study limitations

This study focuses on the self-reported socio-demographics, travel behavior, attitudes and perceptions, and stated preferences of a sample of residents from four California metropolitan regions. The survey sampling strategy was designed to capture a representative sample from each metropolitan region surveyed based on regional univariate distributions of each socio-demographic variable (see Table 2 and Table A2). Some of the socio-demographic targets were relaxed during the survey distribution process in order to reach the sample target size, resulting in differences of about 10% between the sample income distribution and the population across the four metropolitan regions surveyed. Analyses of TNC travel behavior and demand sensitivity are disaggregated by income to explicitly account for this small discrepancy in the socio-demographic representativeness of the study sample. Moreover, we note that the

[3] A significance level of 95% was used in for the likelihood ratio test.

multivariate distributions of socio-demographic variables were not explicitly accounted for, further limiting the similarity between the sample and the population in any particular region.[4]

While all four metropolitan regions examined reside in California, there are distinct differences in the land use, culture, and transportation systems that are reflected in the survey results. All survey analysis results are disaggregated by metropolitan region and the significance of findings are noted separately for each region, when applicable. Since the sample from the Los Angeles region is about five times the size of the other three regions, the margin of error for results from Los Angeles is about 2%, while the margin of error of the remaining regions is about 6%. In addition, the TNC choice model produced by the DCA includes region-specific parameter estimates, which reflect the heterogeneity in demand sensitivity across the regions.

Both TNC users and nonusers are included in the DCA. As a result, the TNC choice model may be used to understand demand sensitivity with respect to TNC-ride options across the full population in any of the metropolitan regions studied, both at present and in hypothetical scenarios in which various circumstances (e.g., the proliferation of SAVs, fuel price changes, etc.) or policies (e.g., TNC surcharges, road pricing, targeted subsidies, etc.) have an impact on the price and time tradeoffs in choosing between TNC-ride options. However, it is important to note that the TNC mode choice model alone does not predict the likelihood that an individual will choose to use a TNC over other modes – it merely predicts which TNC-ride option would be preferred in the event that a traveler is considering using a TNC for a particular trip.

Finally, we note that SP surveys are limited in their ability to predict the actual choices of individuals in their day-to-day travel. In the absence of reservation-level data from on-demand mobility providers or costly travel diary survey data, SP surveys provide a means of understanding individuals' choices through controlled experiments. The trip context and alternative-specific variables in the SP experiments were designed to control for as many pertinent factors in the decision-making process of choosing between on-demand ride options as possible. With the exception of the attitudes and perception variables, all parameters in the model are routinely captured by household travel surveys, which are commonly used for regional travel demand modeling.

5. Results

In this section, the results of the survey analysis and DCA are presented, with an emphasis on developing an understanding of the opportunities and challenges to increasing the pooling market.

5.1. Respondent demographics

By design, the survey sample is close to socio-demographically representative of the populations in the Los Angeles, Sacramento, San Diego, and San Francisco Bay Area metropolitan regions, as reported by the 2017 five-year American Community Survey (ACS) estimates (United States Census Bureau, 2018). As shown in Table 2 below, the sample distributions of gender and age most closely match those of the general population, across all metropolitan regions surveyed. Across all of the regions, the lowest and highest income groups are over- and undersampled, respectively, with respondents earning less than $35,000 annually making up about 6% to 10% more of the sample than the population and those earning $100,000 or more annually making up about 6% to 12% less than the population.

The sample distributions of educational attainment and race/ethnicity (see Table A2) are similar to those of the general population, with a few exceptions: 1) the respondent samples from the Los Angeles metropolitan region with less than a high school degree and those with a Bachelor's degree are undersampled, while the remaining two educational attainment groups are oversampled, and 2) White/Caucasian respondents are oversampled by up to 8% compared to the population across the Sacramento, San Diego, and San Francisco Bay Area metropolitan regions.

5.2. TNC trip frequency

Active TNC users comprise just over one half of the population in all metropolitan regions except in Sacramento, where only 44% of the population has used TNCs locally in the past year. Henceforth, we refer to respondents that have used TNCs (e.g., Lyft, Uber) in their metropolitan region at least once in the year prior as TNC users and those that have not as nonusers. The distributions of age, education, and income (see Table 2 and Table A2) suggest that active TNC users are generally younger and wealthier than nonusers, across all of the metropolitan regions surveyed. Interestingly, we found no significant difference in the likelihood of being an active user based on vehicle ownership across all regions except for the San Diego region, where active TNC users were about half as likely as nonusers to not own a vehicle but twice as likely as nonusers to own three or more vehicles. Respondents that have a medical condition or handicap that makes it challenging to travel outside of the home make up about 10% to 12% of the sample across all of the metropolitan regions. Respondents with a medical condition/handicap are significantly less likely to be active TNC users in the Los Angeles and Sacramento metropolitan regions, while they are slightly more likely to be active TNC users in the San Francisco Bay Area, where 60% of respondents with a medical condition/handicap are active TNC users.

Heavy TNC users – those that use TNCs more than three times per week—pose the largest opportunity for achieving policy objectives through TDM strategies that incentivize pooling. Although *heavy TNC users* constitute a relatively small portion of the overall

[4] The correlations between socio-demographic variables are presented in the Appendix, Table A3.

Table 2
Distribution of Socio-Demographics of the Population and the Survey Sample by Metropolitan Region.

	LOS ANGELES			SACRAMENTO			SAN DIEGO			SAN FRANCISCO BAY AREA		
GENDER	Population[a] N = 10,271,191	Survey N = 1,541	TNC Users n = 808	Population[b] N = 1,300,405	Survey N = 294	TNC Users n = 128	Population[c] N = 2,555,203	Survey N = 297	TNC Users n = 155	Population[d] N = 6,026,055	Survey N = 292	TNC Users n = 162
Male	49%	49%	47%	48%	46%	47%	50%	50%	47%	49%	47%	46%
Female	51%	51%	53%	52%	53%	52%	50%	50%	53%	51%	52%	54%
Other	n/a	0.3%	0.1%	n/a	0.7%	1.5%	n/a	0%	0%	n/a	0.7%	0.6%
AGE (years old)	N = 10,271,191	N = 1,549	n = 810	N = 1,300,405	N = 295	n = 130	N = 2,555,203	N = 298	n = 155	N = 6,026,055	N = 292	n = 162
18 to 29	23%	26%	31%*	24%	22%	23%	25%	22%	26%	20%	23%	31%*
30 to 49	36%	40%*	42%	35%	30%	40%*	35%	39%	45%	37%	31%	39%*
50 to 69	29%	26%	22%*	30%	36%	32%	29%	29%	23%	31%	33%	22%*
70 and over	11%	8%*	4%*	11%	13%	5%*	11%	10%	6%	12%	13%	8%*
INCOME	N = 4,315,854	N = 1,505	n = 793	N = 604,895	N = 289	n = 127	N = 1,112,851	N = 294	n = 153	N = 2,700,986	N = 281	n = 156
Less than $35,000	28%	36%*	35%	29%	36%	33%	24%	34%*	25%*	20%	26%	27%
$35,000 - $99,999	40%	42%	41%	43%	41%	40%	41%	44%	47%	34%	39%	36%
$100,000 - $199,999	23%	18%*	19%	22%	18%	20%	25%	19%	23%	29%	26%	24%
$200,000 or more	10%	5%*	5%	6%	4%	7%	9%	4%*	5%	18%	9%*	13%
VEHICLE OWNERSHIP	N = 4,320,174	N = 1,549	n = 810	N = 604,895	N = 295	n = 130	N = 1,111,739	N = 298	n = 155	N = 2,700,986	N = 292	n = 162
0	8%	11%*	12%	7%	10%	10%	6%	12%*	8%	10%	15%*	15%
1	33%	41%*	41%	34%	43%*	45%	31%	40%*	40%	31%	38%	38%
2	37%	34%	35%	37%	35%	33%	40%	38%	38%	36%	32%	32%
3	14%	8%*	8%	15%	9%*	8%	16%	8%*	9%	15%	8%*	7%
4 or more	8%	5%*	5%	7%	3%	5%	8%	2%*	5%	8%	7%	7%

Asterisks in the: 1) survey and 2) TNC user columns denote a 99% confidence level in the difference in proportions of each socio-demographic variable between the: 1) population and survey sample and 2) survey sample and TNC users, respectively.
a. Los Angeles-Long Beach-Anaheim, CA Metro Area
b. Sacramento and Yolo Counties, CA
c. San Diego-Carlsbad, CA Metro Area
d. Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties, CA

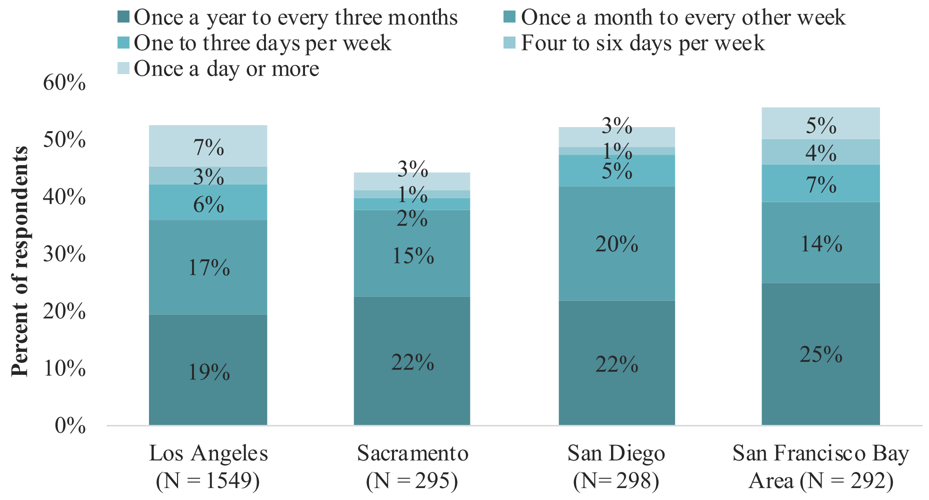

Fig. 2. Distribution of TNC Trip Frequency by Metropolitan Region.
*Heavy TNC Users.

population across the four metropolitan regions surveyed (see Fig. 2 above), they represent a cohort of TNC users that will be among the most impacted by any such policies, as they have incorporated on-demand ride services into their weekly routine beyond just weekend travel and are likely to consider on-demand rides in their mode choice decisions on a daily basis. In particular, a majority of daily TNC users are making more than one TNC trip per day, across all of the regions surveyed.

Heavy TNC users are disproportionately young, low income, and are more likely to not own or lease a car. Fig. 3 below shows the percent of respondents in different age groups that use TNCs one to three days a week, four to six days a week, and once a day or more in each metropolitan region. The *heavy TNC user* segment is particularly young in the San Francisco Bay Area, where roughly one in four respondents under the age of 30 use TNCs more than three days a week, while about one in six use TNCs on a daily basis. Respondents under the age of 30 are about twice as likely as those aged 30 to 49 years old to use TNCs more than three days a week in the San Francisco Bay Area, and they are about 1.7 times as likely in the Los Angeles and San Diego metropolitan regions.

Respondents in the lowest income group—those earning less than $35,000 a year – are the most likely to use TNCs on a weekly and

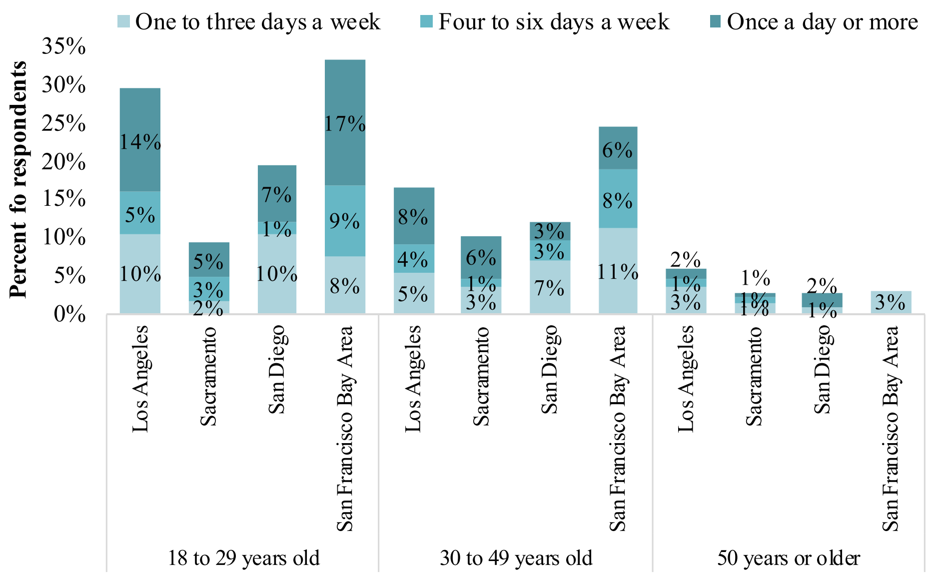

Fig. 3. Distribution of TNC Trip Frequency by Age and Metropolitan Region.
*Heavy TNC Users.

daily basis, across all metropolitan regions. Although respondents with $35,000 or less of annual income comprise about one third of TNC users in the Los Angeles and Sacramento samples and about one quarter of TNC users in the San Diego and San Francisco samples, about 70% of daily TNC users in San Diego and Sacramento and about 55% and 40% of daily TNC users in San Francisco and Los Angeles, respectively, have an annual income of less than $35,000. Across the Los Angeles, Sacramento, and San Francisco Bay Area metropolitan regions, respondents that do not own or lease a vehicle are more likely to use TNCs on a weekly basis than are vehicle owners. One in four non-vehicle owners from these three metropolitan regions uses TNCs once a week or more (see Fig. A1). Interestingly, cross-tabulations of income and the frequency of TNC use suggest that frequent TNC use among the lowest income group in the Los Angeles and Sacramento regions may be similarly linked to a lack of vehicle ownership. In contrast, in the San Diego and San Francisco regions, low-income vehicle owners are more likely to use TNCs on a daily basis than low-income earners that do not own a vehicle.

Heavy TNC use also varies notably across race and ethnicity, reflecting the differences in socio-economic disparities across racial and ethnic groups in each metropolitan region studied (see Fig. A2). In aggregate, Caucasians/Non Hispanics are significantly less likely to be heavy TNC users than all other racial/ethnic groups in both the San Diego and Sacramento regions, while Asians are the least likely to be heavy TNC users in the Los Angeles region. In the San Francisco Bay Area, African Americans are significantly more likely to be heavy TNC users compared to Asians and Caucasians/Non Hispanics. This is due to a particularly high rate of heavy TNC use (44%) among African Americans earning less than $35,000 a year in the San Francisco Bay Area. Among this income group, African Americans are about twice as likely as Caucasians and Hispanics and four times as likely as Asians to be heavy TNC users. African Americans are also the most likely to be heavy TNC users among those earning less than $35,000 in the Los Angeles and Sacramento metropolitan regions, followed by Hispanics in Los Angeles and both Hispanics and Asians in Sacramento. In San Diego, Asians in this lowest income group are the most likely to be heavy TNC users with a rate of 20% followed by Hispanics with a rate of 10%, while no Caucasian/Non Hispanics nor African Americans in this region were heavy TNC users. In the middle income group (earning $35,000 to $50,000 annually), Hispanics were the most likely to be heavy TNC users in both the Sacramento and San Diego regions, while few to no individuals in the other racial/ethnic groups earning the same amount in those two regions were heavy TNC users. In Los Angeles, Caucasians/Non Hispanics followed closely by African Americans are the most likely to be heavy TNC users among the middle income group.

The general TNC use trends with respect to age hold across each racial/ethnic group, although the confluence of age, income, and race/ethnicity become apparent when focusing on the distribution of heavy TNC users across race ethnicity in each age group. In particular, heavy TNC use among young people reflects higher usage among: (1) higher income young Caucasian/Non Hispanics and (2) lower income African Americans. About 30% of African Americans and 25% of Caucasian/Non Hispanics aged 18 to 29 years old use TNCs more than three days a week, compared to about 15% of Hispanics and about 10% of Asians in this same age group.

5.3. TNC user travel profiles

The travel profiles of respondents vary significantly across the regions surveyed, reflecting regional differences in the availability of public transit and shared mobility services. Public transit use is highest in the San Francisco Bay Area and Los Angeles metropolitan regions, where about one third and one quarter of all respondents use some form of public transit once a week or more, respectively. In contrast, only about 15% of respondents in the Sacramento and San Diego regions use public transit on a weekly basis. Both the San Francisco Bay Area and the Los Angeles metropolitan regions have rapid transit systems (e.g., Bay Area Rapid Transit (BART) District, Los Angeles Metro Rail Purple and Red lines) in addition to light rail systems, which are available in all four of the regions studied. While about 5% of respondents use their local light rail system on a weekly basis across all regions, about 15% and 20% of respondents in the Los Angeles region and the San Francisco Bay Area use the Metro Rail and BART systems, respectively. Only about one percent of respondents in the Los Angeles, San Diego, and San Francisco Bay Area regions use their local commuter rail systems on a weekly basis, while there were no weekly commuter rail users among the respondents from the Sacramento region. The rate of public bus use follows a similar trend to that of rail, with weekly bus users making up about 27%, 20%, 16%, and 11% of respondents in the San Francisco Bay Area, Los Angeles, San Diego, and Sacramento metropolitan regions, respectively.

Across all metropolitan regions surveyed, frequent TNC users reflect more multimodal travel behavior than other respondents. Table 3below presents the distribution of transportation modes used at least once a week by respondents that use TNCs once a month to once every other week (monthly TNC users) and those that use TNCs at least once a week (weekly TNC users) in each of the four metropolitan regions. It is important to note that these results do not imply causality between increased TNC use and the use of other modes or vice versa.

While there is little to no significant difference in the weekly drive alone rate across respondents with varying TNC use frequencies, weekly TNC users are significantly more likely than monthly TNC users to use the public bus and shared micromobility (i.e., shared docked and dockless bikes and scooters) on a weekly basis across all four of the metropolitan regions except Sacramento, where there were no weekly shared micromobility users among monthly and weekly TNC users. Only about 1% to 3% of all respondents in each metropolitan region used shared micromobility services on a weekly basis, and in the Sacramento region, all weekly shared micromobility users were using the JUMP dockless electric bikesharing system. Please note that Uber invested $170 million in Lime and transfered the JUMP division to Lime in May 2020. Shared dockless electric scooters, which were not available in the Sacramento region at the time of the survey, accounted for about 40% of weekly shared micromobility use in the San Francisco Bay Area and about 50% and 75% in the Los Angeles and San Diego metropolitan regions, respectively. Again, it is important to note that weekly shared micromobility use is quite low among total respondents, at just 1% to 3% in each of the four metropolitan areas surveyed. Taxi use was similarly low across all metropolitan regions, with weekly taxi users making up less than 2% of all respondents and about 6% to 10% of

Table 3
Distribution of Modes Used at Least Once a Week by TNC Trip Frequency and Metropolitan Region.

	LOS ANGELES		SACRAMENTO		SAN DIEGO		SAN FRANCISCO BAY AREA	
	Monthly TNC Users n = 258	Weekly TNC Users n = 252	Monthly TNC Users n = 45	Weekly TNC Users n = 19	Monthly TNC Users n = 60	Weekly TNC Users n = 30	Monthly TNC Users n = 41	Weekly TNC Users n = 48
Drive alone	83%	84%	82%	74%	92%*	87%	78%	69%
Carpool/ Vanpool	9%	25%***	9%	21%	3%	17%**	10%	17%
Public bus	16%**	55%***	16%	42%**	10%	40%***	29%	69%***
Rail	14%*	49%***	9%**	16%	10%*	7%	32%	52%*
Walk (to a destination)	50%	73%***	62%***	74%	60%**	77%	63%*	71%
Personal bicycle	5%	6%	11%	5%	5%	3%	2%	4%
Shared micromobility (i.e., shared bikes and scooters)	2%	5%**	0%	0%	0%	10%**	0%	17%***

Asterisks in the 1) Monthly TNC Users and 2) Weekly TNC Users columns denote a significant difference in the proportions of weekly mode use between: 1) monthly TNC users and respondents that use TNC less than once a month and 2) monthly and weekly TNC users, respectively.
* : p-value < 0.1; ** : p-value < 0.05; *** : p-value < 0.01

weekly TNC users.

Across all metropolitan regions, weekly public transit users are significantly more likely to use TNCs on a weekly basis than are less frequent public transit users. About 40% of weekly public transit riders in the San Francisco Bay Area and Los Angeles regions use TNCs on a weekly basis, while only about 25% of those in the Sacramento and San Diego regions do so. Interestingly, the rate of weekly TNC use is about the same across weekly riders of bus and rail systems, with the exception of weekly light rail riders in the San Francisco Bay Area, who are significantly less likely than weekly bus and rapid transit riders to use TNCs on a weekly basis. These results are consistent with the findings from previous research using a convenience sample of public transit riders of four agencies, including BART, which found that about half of weekly TNC users also rode public transit on a weekly basis (Feigon and Murphy, 2018).

Finally, we observe that in the Los Angeles and San Diego regions, weekly TNC users were significantly more likely than monthly TNC users to carpool/vanpool on a weekly basis. With the exception of the Los Angeles region, the weekly carpool/vanpool rates in the respondent samples were about 50% lower than the corresponding ACS 2017 estimated ridesharing commute mode shares for the study regions (U.S. Census Bureau, 2018a). Interestingly, we observe significantly higher rates of weekly carpool/vanpool use among weekly TNC users across all regions, with about half of weekly TNC users in the Los Angeles and San Francisco Bay Area metropolitan regions and about 30% and 25% of weekly TNC users in the Sacramento and San Diego metropolitan regions, respectively, carpooling/vanpooling on a weekly basis.

5.4. TNC trip purpose

To further the understanding of TNC utility to different population segments, TNC trip purpose is examined. TNC users were asked to identify what trip purposes they use TNCs for in their metropolitan region. Consistent with previous TNC studies of user behavior, the most popular trip purposes among active TNC users across all metropolitan regions include: 1) traveling to or from restaurants or bars, 2) other social or recreational activities, and 3) airport travel. Weekly TNC users are significantly more likely to use TNCs to: 1) commute to or from work or school, 2) attend work-related meetings, 3) go grocery shopping, and 4) visit friends or relatives than are less frequent users. In addition, weekly TNC users in the Los Angeles and San Francisco Bay Area regions are significantly more likely to: 1) pickup or dropoff children and 2) go to or from healthcare services. About 40% of weekly TNC users in the San Diego metropolitan region, about 30% in the Los Angeles and San Francisco Bay Area regions, and about 20% in the Sacramento region use TNCs to commute to or from work or school, and about 15% to 20% of weekly users use TNCs for work-related travel during the day, across all metropolitan regions.

The portion of monthly and weekly TNC users that use TNCs to connect to/from public transit stations is notably lower than the portion of those that use public transit on a weekly basis, across the four metropolitan regions studied. Only about one quarter of all weekly public transit users report using TNCs to go to/from public transit stations, with little variation across weekly users of public bus and rail services. One exception is commuter rail riders in the Los Angeles metropolitan region, who are more likely to report using TNCs to connect to public transit than other public transit users in their region. In the Sacramento and San Francisco Bay Area, there is no significant difference between the portion of monthly and weekly TNC users that use TNCs to go to/from public transit stations, with only about 10% and 20% of these users doing so in each region, respectively. In contrast, about 10% of monthly TNC users in the Los Angeles and San Diego regions use TNCs to connect to public transit stations, while about 20% and 30% of weekly TNC users do so in each region, respectively. In future research, the authors plan to investigate the contextual and operational factors in traveler choice between TNCs and public transit.

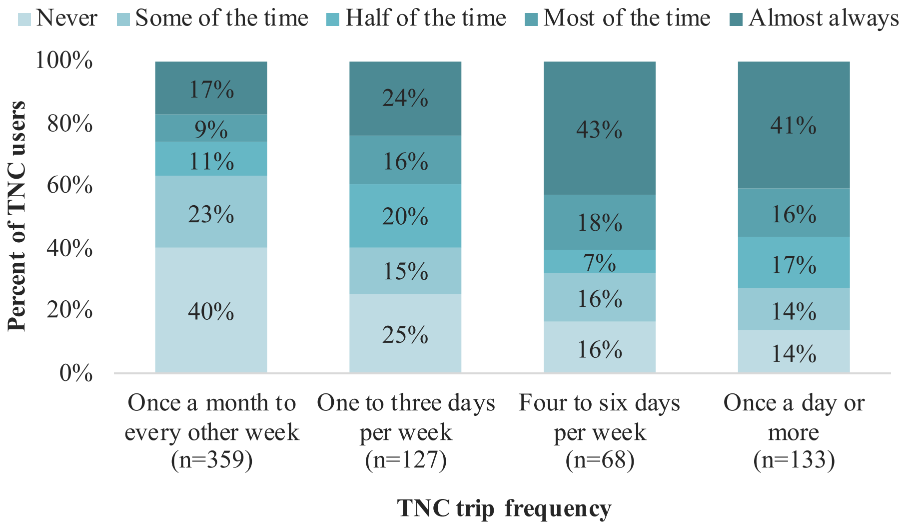

Fig. 4. Distribution of How Often TNC Users Consider Using Shared TNC Options by Frequency of TNC Use.
*Heavy TNC Users.

5.5. *Propensity to consider pooling*

Next, TNC pooling is examined. TNC users were asked how often they consider using the shared ride options (e.g., UberPool, Uber Express POOL, or Lyft Shared rides (formerly Lyft Line)) when using TNCs. Across all metropolitan regions in which shared ride options were available at the time of the survey, about 30% of TNC users consider using shared-ride options more than half of the time that they use TNCs, while about 60% say they consider sharing less than half of the time. Across all metropolitan regions with shared TNC ride services,[5] infrequent TNC users are the least likely to consider shared-ride options when using TNCs. The majority of respondents that use TNCs less than once a month consider sharing their rides less than half the time. As displayed in Fig. 4 above, *heavy TNC users* are significantly more likely to consider sharing TNC rides than less frequent users. Across all metropolitan regions, the portion of users that never consider pooling when using TNCs decreases with trip frequency.

5.6. *Discrete choice analysis*

This section explores the mode choice model estimation. The model has a null log likelihood value of −10,897.14. The log likelihood of the final model is – 9,237.41, with pseudo r-squared and r-bar-squared values of 0.152 and 0.145, respectively.

The final model specification is presented in Table 4 below. The estimated time and cost parameters are all generic across alternatives, thus the coefficient estimates of those variables are the same across all three TNC alternatives (i.e., ride-alone, door-to-door shared ride, and indirect shared ride). The remaining parameters are specified with the ride-alone TNC alternative as the base (the ride-alone coefficients for these parameters are set equal to zero), and they are either generic across the shared ride options (e.g., the promotional offer parameters) or alternative-specific, with a separate coefficient estimated for door-to-door and indirect shared rides. Where applicable, region-specific parameter coefficients are shown side-by-side in the table, spanning the columns that correspond to the metropolitan region for which the parameter is specified. For example, the trip destination parameter for public transit station-bound trips is specified for each metropolitan region separately, while the 30 to 50 years of age group parameter is specified using three coefficients for each shared-ride alternative according to three regional groupings: 1) Los Angeles metropolitan region, 2) Sacramento and San Diego regions, and 3) San Francisco metropolitan region. The latter parameter specification indicates that there is a significant difference in the demand sensitivity for shared TNC rides across the three metropolitan region groupings, but no significant difference across the Sacramento and San Diego metropolitan regions.

The coefficient estimates for the alternative specific constant (ASC) parameters indicate that, all else equal, individuals have a large, highly significant preference for the ride-alone TNC option over either shared ride option. There is also a slight preference for the door-to-door over the indirect shared ride option.

5.7. *The sensitivity of pooling demand to travel time, cost, and promotional offers*

The TNC demand sensitivities with respect to travel time and cost provide invaluable insight into the tradeoffs of travelers when

[5] Note: pooled TNC services were not available in the Sacramento metropolitan region at the time of the survey.

Table 4
TNC Mode Choice Model Results.

<table>
<tr><th rowspan="2"></th><th colspan="4">DOOR-TO-DOOR SHARED RIDE</th><th colspan="4">INDIRECT SHARED RIDE</th></tr>
<tr><th>LOS ANGELES</th><th>SACRA-MENTO</th><th>SAN DIEGO</th><th>SAN FRANCISCO BAY AREA</th><th>LOS ANGELES</th><th>SACRA-MENTO</th><th>SAN DIEGO</th><th>SAN FRANCISCO BAY AREA</th></tr>
<tr><td>Constants</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Alternative-Specific Constant (ASC)</td><td colspan="4">-1.493***</td><td colspan="4">-1.409***</td></tr>
<tr><td>Estimated Travel Time</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Wait time (minutes)</td><td>-0.033***</td><td>-0.025*</td><td>-0.033***</td><td>-0.052***</td><td>-0.033***</td><td>-0.025*</td><td>-0.033***</td><td>-0.052***</td></tr>
<tr><td>Walk time (minutes)</td><td colspan="4">n/a</td><td>-0.016</td><td>-0.072***</td><td colspan="2">-0.042**</td></tr>
<tr><td>In-vehicle time (minutes) – Income less than $100,000</td><td>-0.008**</td><td>-0.012**</td><td>-0.012*</td><td>-0.012**</td><td>-0.008**</td><td>-0.012**</td><td>-0.012*</td><td>-0.012**</td></tr>
<tr><td>In-vehicle time (minutes) – Income $100,000 or more</td><td>-0.021***</td><td>-0.031***</td><td>-0.012*</td><td>-0.031***</td><td>-0.017***</td><td>-0.031***</td><td>-0.012*</td><td>-0.031***</td></tr>
<tr><td>Estimated Cost</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Cost ($)</td><td>-0.022***</td><td>-0.035***</td><td>-0.029***</td><td>-0.032***</td><td>-0.022***</td><td>-0.035***</td><td>-0.029***</td><td>-0.032***</td></tr>
<tr><td>Promotional Offer</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Type 1 (% off of next ride)</td><td colspan="4">0.013***</td><td colspan="4">0.013***</td></tr>
<tr><td>Type 2 (1/# of rides to get one free)</td><td colspan="4">0.47**</td><td colspan="4">0.47**</td></tr>
<tr><td>Type 3 ($ off of transit fare)</td><td colspan="4">0.060*</td><td colspan="4">0.060*</td></tr>
<tr><td>Trip Origin [Home]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Somewhere other than home</td><td colspan="4">0.072</td><td colspan="4">0.203**</td></tr>
<tr><td>Trip Destination [Home]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Restaurant/Bar</td><td colspan="4">0.329***</td><td colspan="4">0.173*</td></tr>
<tr><td>Airport</td><td colspan="4">0.245*</td><td colspan="4">0.153</td></tr>
<tr><td>Public transit station</td><td>0.228*</td><td>0.211</td><td>-0.002</td><td>0.513**</td><td>0.228*</td><td>-0.449</td><td>-0.002</td><td>0.513**</td></tr>
<tr><td>Work</td><td colspan="4">0.485***</td><td colspan="4">0.485***</td></tr>
<tr><td>Social/Recreational activity</td><td colspan="4">0.190*</td><td colspan="4">0.190*</td></tr>
<tr><td>Time Sensitivity [Some/plenty of time to spare]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>No time to spare</td><td colspan="4">-0.360***</td><td colspan="4">-0.595***</td></tr>
<tr><td>Gender [Male]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Female</td><td colspan="4">0.084</td><td colspan="4">0.253***</td></tr>
<tr><td>Age [18 to 29 years old]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>30 to 50 years old</td><td>-0.119*</td><td colspan="2">0.124</td><td>-0.444**</td><td>-0.119*</td><td colspan="2">0.124</td><td>-0.444**</td></tr>
<tr><td>50 to 70 years old</td><td colspan="3">0.082</td><td>-0.325*</td><td colspan="3">0.082</td><td>-0.325*</td></tr>
<tr><td>70 years or older</td><td colspan="2">-0.037</td><td>0.377</td><td>-0.240</td><td colspan="2">-0.157</td><td>0.704**</td><td>-0.359</td></tr>
<tr><td>Employment Status [Unemployed/Retired]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Employed/Student</td><td colspan="4">-0.218**</td><td colspan="4">-0.218**</td></tr>
<tr><td>Income [$35,000 to $99,999]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Less than $35,000</td><td colspan="4">0.041</td><td colspan="4">0.073</td></tr>
<tr><td>$100,000 or more</td><td colspan="4">-0.153*</td><td colspan="4">-0.346***</td></tr>
<tr><td>Medical Condition/Handicap [None]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Medical Condition/Handicap</td><td colspan="4">0.395***</td><td colspan="4">-0.232*</td></tr>
<tr><td>Car Ownership [Non-owner]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Vehicle owner</td><td>0.603***</td><td>-0.114***</td><td colspan="2">0.603***</td><td>0.346**</td><td>-0.371**</td><td colspan="2">0.346**</td></tr>
<tr><td>Mobility Profile [Use mode less than once a week]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Drive alone</td><td>-0.299***</td><td>0.638**</td><td colspan="2">-0.299***</td><td>-0.299***</td><td>0.638**</td><td colspan="2">-0.299***</td></tr>
<tr><td>Public bus</td><td colspan="4">0.125*</td><td colspan="4">0.125*</td></tr>
<tr><td>Rail</td><td colspan="4">0.099</td><td>-0.482***</td><td colspan="3">0.695***</td></tr>
<tr><td>Carpool/Vanpool</td><td colspan="4">0.463***</td><td colspan="4">0.463***</td></tr>
<tr><td>Shared micromobility</td><td colspan="4">0.497**</td><td colspan="4">0.497**</td></tr>
<tr><td>TNC Use [Use TNCs less than once a year]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Use TNCs once a year to once every other month</td><td colspan="4">0.121</td><td colspan="4">0.121</td></tr>
<tr><td>Use TNCs once a month to once every other week</td><td colspan="4">-0.017*</td><td colspan="4">-0.017*</td></tr>
<tr><td>Use TNCs one to three times per week</td><td colspan="4">0.357***</td><td colspan="3">0.357***</td><td>-0.967***</td></tr>
<tr><td>Use TNCs more than three times per week</td><td colspan="4">0.170</td><td colspan="3">-0.157***</td><td>-1.482***</td></tr>
<tr><td>TNC tenure (years since started using TNCs)</td><td colspan="4">0.030*</td><td colspan="4">0.030*</td></tr>
<tr><td>Attitudes/Perceptions [Never]</td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Enjoy chatting with driver: Nonusers</td><td colspan="4">-0.156***</td><td colspan="4">-0.157***</td></tr>
<tr><td>Uncomfortable sharing rides with strangers: Users and Nonusers</td><td colspan="4">-0.233***</td><td colspan="4">-0.233***</td></tr>
<tr><td>Enjoy chatting with other passengers: Users</td><td colspan="4">0.126***</td><td colspan="4">0.136***</td></tr>
<tr><td>Enjoy chatting with other passengers: Nonusers</td><td colspan="4">0.250***</td><td colspan="4">0.250***</td></tr>
<tr><td>Believe shared rides are more environmentally friendly than ride-alone TNCs: Users</td><td colspan="3">0.084**</td><td>0.220**</td><td colspan="3">0.154***</td><td>0.290***</td></tr>
</table>

* : p-value < 0.1; ** : p-value < 0.01; *** : p-value < 0.001

choosing between TNC ride options for a particular ride. In the Los Angeles metropolitan region, TNC mode choices are most sensitive to estimated wait time, whereas travelers in the Sacramento and San Diego metropolitan regions are most sensitive to walking time. In contrast, those in the San Francisco Bay Area are almost indifferent between walking and wait time. The model reflects a significant difference in the sensitivity of demand to in-vehicle time across income groups in all metropolitan regions surveyed, except for San Diego. In the other three regions, travelers earning $100,000 or more annually were about twice as sensitive to in-vehicle time as those earning less than $100,000. The alternative-specific specifications for the in-vehicle time parameters were also tested to investigate the potential that individuals value their time in a shared vehicle differently than when riding alone. These tests failed, indicating that other explanatory variables in the model capture the sensitivity of preferences across ride options (i.e., trip origin and destination, time sensitivity, socio-demographic and mobility profiles, and attitudes toward sharing and chatting with other passengers).

Fig. 5 below displays the estimated values of different components of TNC travel time. Estimating the same model specification presented in Table 4 without the interaction terms for income and in-vehicle time produced the following estimates of the average values of in-vehicle time for each metropolitan region: $29.18, $27.27, $25.98, and $34.50 for the Los Angeles, Sacramento, San Diego, and San Francisco Bay Area metropolitan regions, respectively. These values are fairly close to the 2018 mean hourly wages in the Los Angeles, Sacramento, San Diego, and San Francisco Bay Area metropolitan regions of $27.83, $27.13, $27.93, and $34.81, respectively (U.S. Bureau of Labor Statistics, 2019). When the in-vehicle time parameter is interacted with income, we observe significantly different values of in-vehicle time for travelers earning above $100,000 per year compared to those earning less, across the Los Angeles, Sacramento, and San Francisco Bay Area metropolitan regions.

In the Los Angeles metropolitan region, the estimated value of walking time is about half the value of wait time. This means that, when choosing between TNC ride options, a traveler in Los Angeles would be indifferent between three additional minutes of walking time and two extra minutes of estimated wait time. In other words, if everything else about two ride options is equal, a traveler in Los Angeles would rather spend their time walking to a pickup or dropoff location than waiting to be picked up. This suggests that the efficient operation of indirect on-demand pooled ride services could play a role in increasing average TNC vehicle occupancy and decreasing total VMT from TNC use, while fostering greater pooling demand. However, this strategy alone may not be successful across all markets, as demonstrated by the very high estimated value of walking time for the Sacramento metropolitan region.

Promotions that offer travelers discounts for future TNC or public transit trips can significantly increase the likelihood that an individual chooses to use a pooled on-demand ride service. Among the three promotional types tested, the offer of a percent discount on a future ride in return for choosing a shared ride resulted in the most significant impact on TNC mode choices. The second promotion type was specified as 1/ # of rides that had to be taken to get one free ride, so the estimated coefficient represents the added utility from an offer of 'take one shared ride get one free.' As one might expect, the positive influence of the promotion on the choice to pool diminishes as more rides are needed to get one free. The third promotion type, which offered a discount off of a public transit fare for choosing to pool to a public transit station, represents an attractive TDM strategy for promoting public transit ridership through improved first mile/last mile connectivity using pooled on-demand rides. Moreover, offering a dollar off of a public transit fare is about twice as effective at increasing the likelihood to pool as taking a dollar off of the estimated cost of a trip.

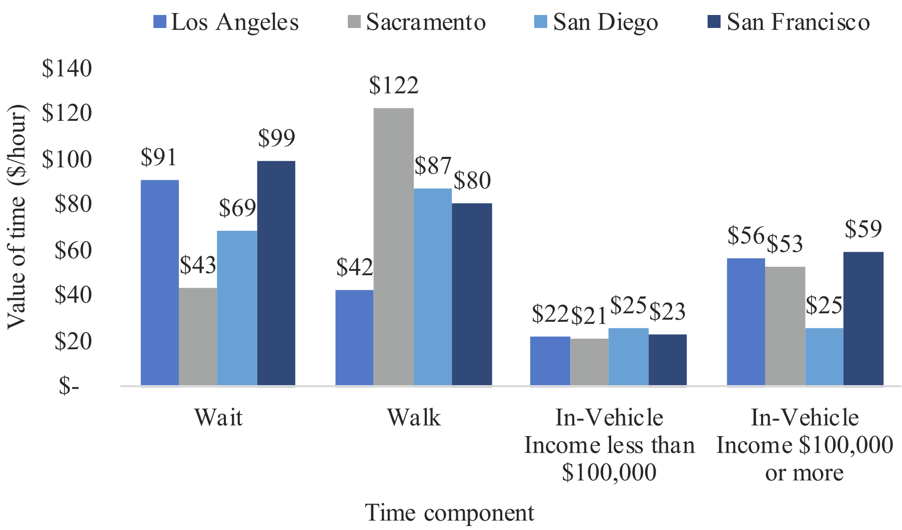

Fig. 5. TNC Mode Choice Model Value of Time Estimates.

5.8. Sensitivity of pooling demand to trip context

The origin and destination of a trip can influence a traveler's preference when choosing between TNC ride options. Travelers are the least likely to choose to pool when starting or ending a trip from their home. When considering TNC options for a trip that starts somewhere other than home, travelers are significantly more likely to choose indirect shared rides, indicating that people may be more willing to walk to a pickup location when they are already away from home. When requesting a ride from home, TNC users are more likely to be better able to use their wait time in a productive manner and thus may be less willing to choose a ride option that requires them to leave their home earlier to walk to a pooled ride.

Compared to all other trip destinations, travelers are generally most likely to prefer to ride alone when making a trip destined for home, and they are most likely to pool when considering TNC options for a commute trip. Travelers in the San Francisco Bay Area are the most likely to choose shared-ride options when linking to a public transit station, whereas linking to transit has no significant influence on preferences for shared rides for those in the San Diego region. While travelers in the Los Angeles and Sacramento metropolitan regions are about as likely to choose a door-to-door shared ride to get to a public transit station as they are for an airport trip, travelers in the Sacramento region have a significant aversion to the indirect shared TNC ride option for transit-linking trips. This result may be dually affected by the lack of exposure to indirect shared rides in the Sacramento region at the time of the survey, as well as important exogenous factors related to the distribution of public transit stations and the surrounding land use in the Sacramento region.

In comparison to home-bound trips, travelers are significantly more likely to share their rides when traveling to a restaurant or bar, although they prefer to use the door-to-door over the indirect shared ride option for such trips. Similarly, there is a significant preference for door-to-door over indirect shared rides for airport trips in which the prospect of carrying luggage while walking to or from a pickup or dropoff location is predictably less attractive than a door-to-door service. Although the coefficient for indirect shared rides to the airport is not significant at a 90% confidence level, the coefficient estimate is relatively large and positive. This might reflect that airport-bound trips tend to be longer in distance than trips to other destinations, which was accounted for in the SP experiment design. Thus, estimated airport trip times and travel costs were greater, on average, than those of other trip purposes, resulting in a greater absolute cost difference between the three TNC ride options. When considering an airport trip, travelers may be particularly sensitive to travel costs as an added expense to airfare and thus be attracted to the large cost savings provided by shared TNC ride options in comparison to the ride-alone TNC option.

The inclusion of the time sensitivity variable in the trip context for each choice experiment allows for the interpretation of the trip purpose coefficient estimates in the model to be independent from assumptions regarding a traveler's relative time sensitivity across trip destinations. The corresponding coefficient estimates reflect the significance of time sensitivity in TNC mode choices by exhibiting a strong preference to ride alone for trips in which there is no time to spare in contrast to those in which there is some or plenty of time to spare. Not surprisingly, travelers are significantly less likely to choose an indirect shared ride over a door-to-door shared ride when they have no time to spare. These results likely reflect exogenous factors corresponding to a traveler's beliefs about the reliability of estimated travel times across shared-ride services.

5.9. Socio-demographic factors in pooling demand sensitivity

The TNC mode choice model enables examination of the differences between individuals presented with identical TNC options under the same trip context. Across all metropolitan regions, females, unemployed or retired individuals, and people with an annual income of less than $35,000 are the most likely to choose a shared ride. In addition, female and low-income travelers are more likely to choose an indirect shared ride, while individuals with an annual income of $100,000 or more are even less likely to choose an indirect shared ride than they are to choose a door-to-door shared ride. In the San Francisco Bay Area, the youngest age group (18 to 29 years old) is the most likely to share an on-demand ride, while the oldest age group (70 years or older) is the most likely to do so in the San Diego metropolitan region. In all metropolitan regions surveyed, except for San Diego, travelers 70 years or older are significantly less likely to choose an indirect shared ride. In San Diego, however, travelers in the oldest age group are even more likely to choose an indirect shared ride than they are to choose a door-to-door shared ride or to ride alone. Investigation of the interaction of income with the age group parameters revealed that the affinity for shared rides among the eldest age group in San Diego is primarily driven by respondents earning less than $35,000 in this age category.

People with a medical condition or handicap are significantly more likely than others to choose a door-to-door shared ride over riding alone. However, they would rather ride alone than take an indirect shared ride, as the need to walk to or from a pickup or dropoff location is particularly burdensome for this population segment. In all metropolitan regions surveyed, except for Sacramento, vehicle owners have a greater preference for pooling than non-vehicle owners, although vehicle owners prefer door-to-door shared rides over indirect shared rides across all metropolitan regions.

The majority of parameters representing race/ethnicity in the mode choice model were found to be insignificant as measured by the asymptomatic t-test. Only the variable for Asians was significant for the Los Angeles and Sacramento regions. These variables indicated that Asians in these regions prefer ride alone over shared TNC services. However, when jointly testing the significance of race/ethnicity variables, the likelihood ratio test is rejected in favor of an unrestricted model without these variables. Thus, the parameters were removed from the model for simplicity and ease of interpretation of the final results.

It is important to note that the discrete choice model represents a linear utility function of the corresponding coefficients for a particular individual in a particular trip context with certain ride options. Thus, an employed 30 to 50 year old who owns one or more cars and has an annual income of $100,000 or more in Los Angeles or San Diego is still more likely to prefer a ride-alone option than would their counterpart (e.g., *unemployed* 30 to 50 year old vehicle owner *earning less than* $100,000/year).

5.10. Pooling demand sensitivity across mobility profiles and TNC use

While vehicle owners are generally more likely to choose a shared ride over riding alone in a TNC, those that drive alone in their vehicle on a weekly basis are significantly less likely to share compared to other people, across all metropolitan regions except for Sacramento. When considering the coefficient estimates for vehicle ownership and weekly drive alone behavior together, it appears across all metropolitan regions that weekly auto drivers have a significant preference for door-to-door shared rides over riding alone in a TNC.

Weekly users of other shared modes are generally more likely to share a ride in a TNC than other travelers. Across all of the metropolitan regions, weekly public bus users are slightly more likely to choose shared rides over riding alone. Weekly rail users, on the other hand, have a significantly large preference for indirect shared rides over either riding alone or using a door-to-door shared ride, across all of the metropolitan regions except for Los Angeles, where weekly rail users have a significant and comparatively large aversion to indirect shared rides. Weekly carpool and/or vanpool use, as well as the use of shared micromobility services on a weekly basis are both strong positive factors in an individual's likelihood to pool. Weekly taxi use did not result in a significant difference in preferences for pooling in TNCs, though we note that the coefficient was slightly negative, as expected.

Likelihood to choose shared rides increases with a traveler's tenure as a TNC user, although it varies with respect to TNC trip frequency. The trend in pooling demand sensitivity with respect to TNC trip frequency suggests that, while TNC weekly users are the most likely to choose a door-to-door shared ride over riding alone, travelers that use TNCs more than three times per week are less likely to do so and actually prefer to ride alone over using indirect shared rides, across all of the metropolitan regions. In the San Francisco Bay Area, where TNC users are likely to have had the most experience with indirect shared rides, weekly TNC users are significantly less likely to choose indirect shared rides compared to riding alone or choosing a door-to-door shared ride. Finally, monthly TNC users do not exhibit a large preference across TNC ride options, although less frequent TNC users have a significant preference for shared rides compared to inactive TNC users and nonusers.

5.11. Pooling demand sensitivity and traveler attitudes and perceptions

The underlying attitudes and perceptions that both TNC users and nonusers have about interactions with drivers and other passengers and the environmental impact of shared-ride TNC services are a significant factor in the sensitivity of demand for pooling. The attitude and perception variables were included in the mode choice model using a Likert scale from zero to four corresponding to responses ranging from 'never' to 'almost always.' There were no significant differences in demand sensitivities to attitudes and perceptions regarding TNC driver and passenger interaction across the door-to-door and indirect shared ride options. Although TNC users are significantly more likely than nonusers to have positive attitudes about chatting with TNC drivers, driver interaction is not a significant factor in their TNC mode choices. On the other hand, nonusers, 40% of whom say they would never or rarely enjoy chatting with TNC drivers, are significantly less likely to pool the more they expect to enjoy chatting with drivers. When it comes to interacting with other passengers, a positive attitude toward sharing a ride and chatting with other passengers has a significant positive effect on pooling preference across TNC users and nonusers. Although there was not a significant difference in pooling demand sensitivity with respect to how comfortable users and nonusers feel about sharing rides with strangers, experience with on-demand rides dampens the increased likelihood for sharing with respect to how much someone enjoys chatting.

TNC user perceptions of the positive environmental impact of shared-ride options significantly increases their likelihood to pool. The impact of these perceptions is stronger for indirect shared rides across all of the metropolitan regions. In the San Francisco Bay Area, the demand sensitivity for pooling is significantly more sensitive to perceptions about the environmental impact of shared rides than in any of the other regions.

6. Policy recommendations and conclusions

Opportunities to expand pooling are diverse and vary across the four metropolitan regions explored in this article. TDM strategies that leverage an understanding of the time and price tradeoffs of travelers under various trip contexts have the potential to increase systemwide vehicle occupancy by incentivizing multiple forms of pooling including: on-demand pooling, app-based ridesharing, microtransit, and traditional public transit. However, careful consideration must be made of regional variations in demand sensitivity to on-demand rides as well as the disparate impacts that such policies may have on marginalized population groups, who are among the most *heavy TNC users*.

Heavy TNC users (those that use TNCs more than three times per week) are disproportionately young, low-income, and non-vehicle owners compared to less frequent TNC users and nonusers. Across all metropolitan regions, the majority of daily TNC users are making multiple TNC trips per day. While *heavy TNC users* are the most likely to consider a shared ride option when using TNC services, they are less likely than weekly users to choose a shared ride when trading off comparable ride-alone, door-to-door shared ride, and indirect shared ride options. Based on their greater propensity to use TNCs for essential trip purposes, there is a sizable opportunity to increase pooling rates among *heavy TNC users* through promotional offers for pooling to public transit stations, employment centers, and healthcare services. In particular, subsidized pooled rides for travelers that are low-income, unemployed, or have a medical condition/

handicap could greatly increase mobility and accessibility for these groups.

However, it is vital to consider the travel time reliability of shared-ride services when targeting pooling incentives at marginalized population groups and highly time sensitive trip purposes. As demonstrated by the history of ridesharing, a critical mass of riders willing to pool is needed to foster convenience and reliability to retain ridership. While the necessary density of pooling ridership may be achieved over time with increased adoption of on-demand mobility and successful TDM strategies, special consideration is necessary for supporting the earliest group of targeted adopters, particularly those who rely the most on shared services and cannot afford the consequences of an unreliable service. Several shared micromobility permit programs have demonstrated a framework for regulating the level of service provided on a geographic basis, typically with the aim of ensuring spatial equity by mandating minimum vehicle availability standards in historically underserved or public transit-poor neighborhoods. Analogous strategies may be developed for on-demand ride services by regulating wait times for particular geographic regions or user groups. The California Public Utilities Commission recently implemented such a regulation for the level of service provided by TNC wheelchair accessible vehicles by establishing response time standards specific to each geographic area of the state (California Public Utilities Code § 5440.5, 2018.).

Indirect shared rides offered by TNCs and microtransit providers pose a substantial opportunity to reduce congestion from single-occupant vehicle use and deadheading. Since indirect pooled rides are designed to minimize deviations from the common path between multiple passengers by requiring that riders walk to and/or from a pickup and/or dropoff location, they can decrease the total travel time of on-demand trips. Moreover, able travelers in some metropolitan regions would rather walk a minute than wait a minute. Thus, by converting waiting time to walking time and reducing in-vehicle time, indirect pooled rides can be a significantly more attractive shared-ride option with co-benefits for society and the environment.

Both curb access management and mileage-based road pricing could serve as effective TDM strategies to increase indirect pooling. In residential and commercial zones, dedicated pickup and dropoff locations for on-demand rides can aid in aggregating demand for indirect ride services, while providing a mechanism for pricing and/or enforcement of desirable curb access restrictions. While mileage-based road pricing can incentivize pooling in general, it can create a particularly large incentive for indirect shared rides, which not only distribute the cost per mile across a larger number of riders but also reduce VMT for any particular trip. In particularly congested conditions that arise frequently in central business districts during peak commute hours, the combination of mileage-based congestion charging with time-dynamical curb access restrictions offers a promising strategy to manage congestion from on-demand rides while incentivizing pooling. Travelers departing from a congested area may be able to save considerable amounts of in-vehicle and wait times by walking to/from a strategically placed pickup/dropoff location that minimizes VMT through congested streets as well as the resulting congestion charges accrued from such a trip. Moreover, on-demand service providers may achieve higher pooling rates by allowing riders to request a hybrid indirect and door-to-door ride. Travelers are more willing to choose an indirect ride when starting a trip from outside their home, but they are least willing to share when taking a trip destined to home. Thus, offering the option to request an indirect ride with a direct dropoff can attract additional pooling demand.

Simple promotions can also provide effective pooling incentives. Offering a discount off of a future ride in return for choosing a pooled ride can be an impactful strategy for reducing VMT during periods of peak or abnormal congestion, such as during rush hour or during a major event. Travelers can also be incentivized to pool across multiple trips by offering a free ride in return for a number of shared rides. This strategy could be particularly effective for incentivizing *heavy TNC users* to try pooling, as there is less risk of inducing additional on-demand rides, while ample opportunities exist for these already captive users to make a shift in their on-demand ride choices. Finally, offering a discount on a public transit fare in return for pooling to a public transit station poses an attractive strategy for increasing public transit ridership through pooled first/last mile connections. Similar incentive policies may be effective for other forms of on-demand shared mobility, such as bikesharing and scootersharing.

However, we observed that the majority of weekly TNC users are not using TNCs in conjunction with public transit. Although public transit use is greatest among high frequency TNC users, the share that access public transit using TNCs is comparatively small. In the Los Angeles and San Francisco Bay Area regions, where about half of weekly TNC users are also weekly rail riders (mostly rapid transit riders) and about 55% and 70% are bus riders, respectively, only about 20% of weekly TNC users in these regions use TNCs to get to/from public transit stations. Previous research has found that faster travel times and reduced wait times are among the top reasons that travelers choose TNCs over public transit (Feigon and Murphy, 2018). More research is needed to discern the trip purposes and contexts in which travelers choose to use a TNC in contrast to a public transit service. Nevertheless, it is clear that there are travelers who regularly access public transit for certain trips and choose to use TNCs for others. Thus, strategies targeted at incentivizing pooled on-demand rides must strike a delicate balance that effectively shifts demand from ride alone to pooled on-demand options, while minimizing further substitution of on-demand rides for public transit. This will be particularly important following the 2020 COVID-19 pandemic in which travelers likely have heightened hygiene and physical distancing concerns associated with shared mobility vehicles, pooling, and public transit use.

Finally, there is tremendous untapped potential to increase the market share of pooling among commuters. We found that the likelihood to pool is greatest for work trips in all metropolitan regions studied except for the San Francisco Bay Area, where trips to public transit have a slightly higher likelihood for pooling. The commuting choice experiments were posed as plan ahead scenarios in which respondents were asked to consider they were planning a trip to work for the following morning. Thus, the increased likelihood to pool for commute trips may also reflect the increased willingness of travelers to pool for trips in which they can reserve a reliable shared ride in advance. This option is currently provided by app-based carpooling services, microtransit services, and TNCs in some pilot areas.

This research suggests that there are key differences in the demand for pooling reflected by the four geographic regions examined in this article, the range of socio-demographic factors, and TNC-service options. Policies should be crafted to reflect the geospatial and socio-demographic differences across regions to encourage pooling and more efficient TNC routing to reduce deadheading and excess VMT. Careful experimentation with pricing strategies and incentives would provide key insights in how to best maximize the societal and environmental benefits of these services and to better prepare for SAV services in the future.

Acknowledgements

This study was made possible through funding received by the University of California Institute of Transportation Studies from the State of California via the Road Repair and Accountability Act of 2017 (Senate Bill 1). The authors would like to thank the State of California for its support of university-based research and especially for the funding received for this project. This research was also made possible by generous funding provided by the Dwight David Eisenhower Transportation Fellowship Program (DDETFP), which is administered by the Federal Highway Administration. The authors would like to thank the U.S. Department of Transportation and Federal Highway Administration for their support of this research.

The authors would also like to thank Professor Joan Walker for her invaluable support in the development of the discrete choice model and Stephen Wong for his assistance with the survey design. Gratitude is also extended to numerous members of the Transportation Sustainability Research Center and the Mobile Sensing Lab for their participation in pre-testing the survey. Finally, the authors would like to thank the members of the project advisory committee for their feedback.

Appendix

(See Figs. A1 and A2. And Tables A1-A3)

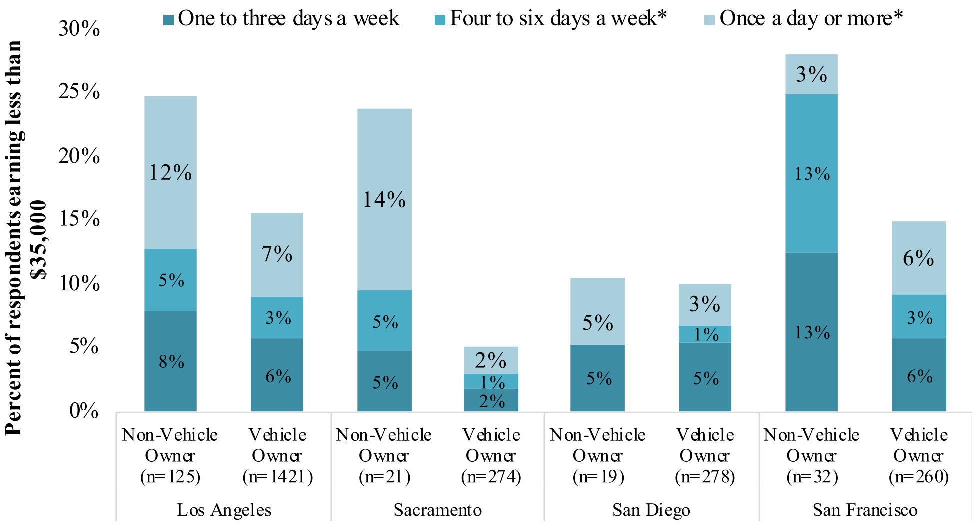

Fig. A1. Distribution of TNC Trip Frequency by Vehicle Ownership and Metropolitan Region.
*Heavy TNC Users.

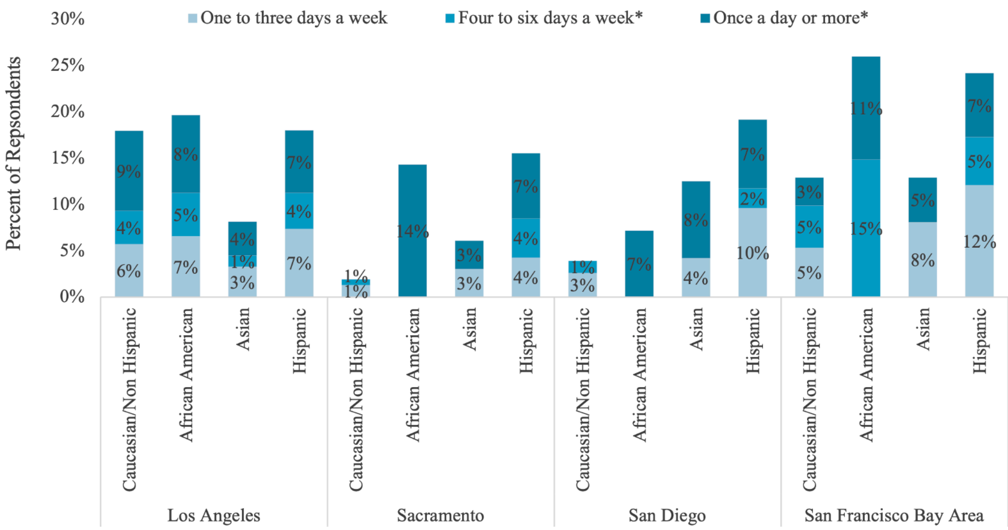

Fig. A2. Distribution of TNC Trip Frequency by Racial/Ethnic Group and Metropolitan Region.
*Heavy TNC Users.

Table A1
Distribution of Alternative-Specific Attribute Levels in the SP Choice Experiments.

	Minimum	Maximum	Mean	Standard Deviation
Estimated wait time (min)				
Ride Alone	2	9	5.7	2.8
Door-to-Door Shared Ride	2	9	5.7	2.9
Indirect Shared Ride	2	9	5.7	2.9
Estimated in-vehicle time (min)				
Ride Alone	7	74	34	22.1
Door-to-Door Shared Ride	7	126	47	32.2
Indirect Shared Ride	7	126	47	32.2
Estimated walking time (min)				
Indirect Shared Ride	2	10	6	2.9
Estimated Cost ($)				
Ride Alone	2.0	173.0	43.5	39.8
Door-to-Door Shared Ride	1.5	157.4	34.1	31.4
Indirect Shared Ride	1.1	143.2	26.7	24.7

Table A2
Distribution of Educational Attainment and Race/Ethnicity of the Population and the Survey Sample by Metropolitan Region.

	LOS ANGELES			SACRAMENTO			SAN DIEGO			SAN FRANCISCO BAY AREA		
EDUCATIONAL ATTAINMENT	N = 10,271,191	N = 1,536	n = 804	N = 1,300,405	N = 291	n = 129	N = 2,555,203	N = 296	n = 155	N = 6,026,055	N = 287	N = 159
High School Diploma or less	40%	33%*	32%	36%	32%	30%	33%	32%	32%	29%	26%	29%
Some College/ Associate's Degree	30%	36%*	36%	36%	41%	40%	33%	35%	37%	28%	32%	31%
Bachelor's Degree	20%	15%*	15%	18%	17%	15%	21%	21%	19%	26%	24%	19%
Graduate/ Professional Degree	10%	16%*	17%	10%	11%	15%	12%	11%	12%	17%	17%	20%
RACE/ETHNICITY	N = 13,261,538	N = 1,532	n = 800	N = 1,708,005	N = 296	n = 128	N = 3,283,665	N = 295	n = 155	N = 4,641,820	N = 292	n = 162
Caucasian/Non Hispanic	30%	29%	25%*	46%	54%*	54%	46%	53%	48%	40%	45%	38%*
African American	6%	7%	7%	9%	5%	7%	5%	5%	4%	6%	9%	10%
Asian	16%	16%	16%	15%	11%	12%	11%	8%	8%	25%	21%	24%
Hispanic	45%	45%	50%*	24%	24%	23%	33%	32%	36%	24%	20%	23%
Two or more	1%	2%*	1%	5%	2%	2%	0%	3%*	0%	4%	0%*	0%
Other	2%	1%*	2%	2%	5%*	2%	2%	1%	4%	1%	4%*	4%

Asterisks in the: 1) survey and 2) TNC users columns denote a 99% confidence level in the difference in proportions of each socio-demographic variable between the: 1) population and survey sample and 2) survey sample and TNC users, respectively.
a. Los Angeles-Long Beach-Anaheim, CA Metro Area
b. Sacramento and Yolo Counties, CA
c. San Diego-Carlsbad, CA Metro Area
d. Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties, CA

Table A3
Correlations Between Respondents' Socio-Demographic Characteristics.

		Female	Age	Income	Education	African American	Asian	Caucasian	Hispanic	Employed	Student	Retired	Vehicles
Los Angeles	Age	−0.12											
	Income	−0.21	0.29										
	Education	−0.20	0.25	0.48									
	African American	0.08	0.09	−0.09	−0.09								
	Asian	−0.05	0.11	0.17	0.27	n/a							
	Caucasian	−0.24	0.29	0.29	0.32	n/a	n/a						
	Hispanic	0.21	−0.39	−0.35	−0.47	n/a	n/a	n/a					
	Employed	−0.03	−0.40	0.02	−0.02	−0.06	0.01	−0.10	0.12				
	Student	0.13	−0.31	−0.19	−0.13	−0.01	−0.07	−0.11	0.15	−0.41			
	Retired	−0.03	0.63	0.09	0.10	0.08	0.03	0.18	−0.23	−0.82	−0.12		
	Vehicles	−0.10	0.16	0.40	0.17	−0.06	0.04	0.07	−0.08	0.03	−0.12	0.05	
	Handicap/Medical Condition	−0.05	−0.03	−0.02	0.04	−0.01	−0.05	0.16	−0.10	−0.03	−0.03	0.04	0.04
San Deigo	Age	0.19											
	Income	0.06	0.27										
	Education	0.21	0.42	0.50									
	African American	−0.05	−0.06	−0.06	−0.09								
	Asian	0.01	−0.08	0.04	0.09	n/a							
	Caucasian	0.30	0.46	0.21	0.34	n/a	n/a						
	Hispanic	−0.33	−0.42	−0.29	−0.44	n/a	n/a	n/a					
	Employed	−0.03	−0.51	−0.07	−0.22	0.02	0.08	−0.25	0.25				
	Student	−0.05	−0.31	−0.11	−0.10	−0.06	0.04	−0.16	0.12	−0.22			
	Retired	0.06	0.65	0.10	0.26	0.00	−0.10	0.32	−0.29	−0.90	−0.16		
	Vehicles	0.01	0.14	0.40	0.21	−0.08	−0.08	0.19	−0.14	−0.05	−0.03	0.07	
	Handicap/Medical Condition	−0.02	0.02	−0.07	−0.13	0.13	−0.02	−0.16	0.08	−0.09	0.05	0.08	−0.19

(continued on next page)

Table A3 (*continued*)

		Female	Age	Income	Education	African American	Asian	Caucasian	Hispanic	Employed	Student	Retired	Vehicles
		Female	Age	Income	Education	African American	Asian	Caucasian	Hispanic	Employed	Student	Retired	Vehicles
Sacramento	Age	0.10											
	Income	−0.07	0.31										
	Education	0.12	0.44	0.44									
	African American	0.09	0.03	−0.10	−0.10								
	Asian	0.10	−0.05	0.01	0.04	n/a							
	Caucasian	0.05	0.50	0.32	0.48	n/a	n/a						
	Hispanic	−0.12	−0.46	−0.29	−0.49	n/a	n/a	n/a					
	Employed	−0.02	−0.58	−0.16	−0.22	0.04	0.00	−0.26	0.24				
	Student	0.01	−0.27	−0.10	−0.22	0.01	0.13	−0.21	0.10	−0.30			
	Retired	0.02	0.73	0.22	0.33	−0.05	−0.08	0.36	−0.27	−0.88	−0.15		
	Vehicles	−0.08	0.10	0.36	0.24	−0.07	−0.01	0.09	−0.07	−0.07	−0.11	0.11	
	Handicap/Medical Condition	−0.03	0.05	−0.03	−0.02	0.11	0.03	0.05	−0.12	−0.01	−0.03	0.02	0.05
San Francisco Bay Area	Age	−0.10											
	Income	0.01	0.19										
	Education	0.07	0.33	0.51									
	African American	0.06	−0.15	−0.22	−0.16								
	Asian	0.06	−0.05	0.07	0.11	n/a							
	Caucasian	−0.01	0.39	0.14	0.34	n/a	n/a						
	Hispanic	−0.06	−0.32	−0.16	−0.42	n/a	n/a	n/a					
	Employed	0.21	−0.48	0.03	−0.02	−0.02	−0.01	−0.13	0.16				
	Student	−0.06	−0.27	−0.02	−0.10	0.06	0.07	−0.14	0.08	−0.25			
	Retired	−0.19	0.59	−0.04	0.05	−0.01	−0.03	0.20	−0.19	−0.92	−0.11		
	Vehicles	−0.08	0.12	0.38	0.13	−0.17	0.06	0.04	−0.03	0.04	0.03	−0.05	
	Handicap/Medical Condition	−0.05	−0.09	−0.07	−0.05	0.05	−0.01	−0.06	0.03	0.10	−0.07	−0.08	−0.16

Pearson's correlation coefficients are shown. The age and vehicles variables are continuous; the income variable is also continuous, using the median income for each income group; the education variable is ordinal; all other variables are binary. The race/ethnicity variables are mutually exclusive.

References

Alonso-Gonzalez, M.J., Oort, N.V., Cats, O., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2020. Value of time and reliability for urban pooled on-demand services. Transportation Research Part C: Emerging Technologies 115 (2020), 102621.

Ben-Akiva, M.E., Lerman, S.R., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press, Cambridge, Ma.

Brown, A. E. (2018). Ridehail Revolution: Ridehail Travel and Equity in Los Angeles. (Doctoral dissertation, University of California, Los Angeles). Retrieved from https://escholarship.org/uc/item/4r22m57k.

Brownstone, D., Small, K.A., 2005. Valuing time and reliability: Assessing the evidence from road pricing demonstrations. Transportation Research Part A: Policy and Practice 39 (2005), 279–293.

California Air Resources Board (CARB) (2019). Clean Miles Standard: 2018 Base-year Emissions Inventory Report. California Air Resources Board. December 2019.

Cervero, R., 1997. Paratransit in America: Redefining mass transportation. Praeger, Westport, Conn.

Chan, N.D., Shaheen, S.A., 2011. Ridesharing in North America: Past, Present, and Future. Transport Reviews. https://doi.org/10.1080/01441647.2011.621557.

Circella, G., Alemi, F., Tiedeman, K., Handy, S., Mokhtarian, P., 2018. The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior. University of California Davis, Institute of Transportation Studies, National Center for Sustainable Transportation.

Circella, G., Matson, G., Alemi, F., Handy, S., 2019. Panel Study of Emerging Transportation Technologies and Trends in California: Phase 2 Data Collection. University of California Davis, Institute of Transportation Studies, National Center for Sustainable Transportation.

California Public Utilities Code § 5440.5 (2018).

Clewlow, R. and G. Mishra (2017). Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States. Institute of Transportation Studies, University of California, Davis, Research Report UCD-ITS-RR-17-07.

Correia, G. and J.M. Viegas (2011). Carpooling and carpool clubs: Clarifying concepts and assessing value enhancement possibilities through a Stated Preference web survey in Lisbon, Portugal. Transportation Research Part A 45 (2011) 81–90.

Cramer, Ju.dd., Krueger, Alan B., 2016. Disruptive change in the taxi business: The case of Uber. The American Economic Review 106 (5), 177–182.

Feigon, S. and C. Murphy (2018). Broadening Understanding of the Interplay Between Public Transit, Shared Mobility, and Personal Automobiles. TCRP Research Report 195. Transportation Research Board, Washington, D.C.

Gehrke, S., A. Felix, and T. Reardon (2018). Fare Choices: A Survey of Ride-Hailing Passengers in Metro Boston. Report #1. Retrieved from: https://www.mapc.org/farechoices/.

Greenblatt, J. and S. Saxena (2015). "Autonomous Taxis Could Greatly Reduce Greenhouse Gas Emissions of U.S. Light-Duty Vehicles," Nature Climate Change 5, pp. 860-863, 2015.

Greenblatt, J. and S. Shaheen (2015). "Automated Vehicles, On-Demand Mobility, and Environmental Impacts," Curr Sustainable Renewable Energy Rep. DOI 10.1007/s40518-015-0038-5.

Hampshire, Robert and Simek, Chris and Fabusuyi, Tayo and Di, Xuan and Chen, Xi, Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX (May 31, 2017). Available at SSRN: https://ssrn.com/abstract=2977969 or http://dx.doi.org/10.2139/ssrn.2977969.

Henao, A., Marshall, W.E., 2018. The impact of ride-hailing on vehicle miles traveled. Transportation. Transportation 2019 (46), 2173–2194. https://doi.org/10.1007/s11116-018-9923-2.

Koppelman, F., Bhat, C., Schofer, J., 1993. Market research evaluation of actions to reduce suburban traffic congestion: Commuter travel behavior and response to demand reduction actions. Transportation Research Part A 27 (5), 383–393.

Lyft (2017). "Save Time With New Pickup Suggestions." Lyft BLOG, Lyft, Inc. Accessed October, 2019. https://blog.lyft.com/posts/2017/6/23/pickup-suggestions.

Lyft (2018). "Get Fare Estimates for Your City – Ride Calculator." Lyft, Inc. Accessed July, 2018. https://www.lyft.com/rider/fare-estimate.
Neoh, J.G., Chipulu, M., and Marshall, A. (2017). What encourages people to carpool? An evaluation of factors with meta-analysis. Transportation. Transportation (2017). 44:423–447 DOI 10.1007/s11116-015-9661-7.
Rayle, L., D. Dai, N. Chan, R. Cervero, and S. Shaheen (2016). "Just A Better Taxi? A Survey- Based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco", in Transport Policy, Volume 45, pp. 168-178. http://dx.doi.org/10.1016/j.tranpol.2015.10.004.
San Francisco County Transportation Authority (SFCTA) (2017). TNCs Today: A Profile of San Francisco Transportation Network Company Activity. Retrieved from: http://www.sfcta.org.
Schaller, B. (2017). Unsustainable? The Growth of App-Based Ride Services and Traffic, Travel and the Future of New York City. Schaller Consulting.
Schaller, B. (2018). The New Automobility: Lyft, Uber and the Future of American Cities.
Shaheen, S.A., Cohen, A., 2019. Shared ride services in North America: definitions, impacts, and the future of pooling. Transport Reviews 39 (4), 427–442. https://doi.org/10.1080/01441647.2018.1497728.
Shaheen, Susan, Stocker, Adam, Lazarus, Jessica, Bhattacharyya, Abhinav, 2016. RideKC: Bridj Pilot Evaluation: Impact, Operational, and Institutional Analysis. Transportation Sustainability Research Center.
Shirgaokar, Manish, Deakin, Elizabeth, 2005. Study of Park-and-Ride Facilities and Their Use in the San Francisco Bay Area of California. Transportation Research Record: Journal of the Transportation Research Board 1927 (1), 46–54. https://doi.org/10.1177/0361198105192700106.
Smith, Aaron, 2016. Shared, Collaborative and On Demand: The New Digital Economy. Pew Research Center.
Train, K., 2009. Discrete Choice Methods with Simulation, second ed. Cambridge University Press, Cambridge.
Uber (2017). A Street Smart POOL Experience for Manhattan. Uber Newsroom, Uber, Inc. Accessed October, 2019. https://www.uber.com/newsroom/manhattanpool.
Uber (2018). "Uber Estimate – Get a Price Estimate in Your City." Uber, Inc. Accessed July, 2018. https://www.uber.com/us/en/price-estimate/.
United States Bureau of Labor Statistics (2019). May 2018 Metropolitan and Nonmetropolitan Area Occupational Employment and Wage Estimates. Retrieved from https://www.bls.gov/oes/2018/may/oessrcma.htm.
United States Census Bureau (2018a). Means of Transportation to Work. 2007-2017 American Community Survey 1-Year Estimates. Washington, DC: U.S. Department of Commerce. Retrieved from https://www.census.gov/programs-surveys/acs/.
United States Census Bureau (2018b). Select Population, Demographic, and Household Estimates, 2017 American Community Survey 5-Year Estimates. Washington, DC: U.S. Department of Commerce. Retrieved from https://www.census.gov/programs-surveys/acs/.
United States Department of Transportation (USDOT) (2016). Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis. Memorandum to Secretarial Officers Modal Administrators. Office of the Secretary of Transportation. Accessed at https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-valuation-travel-time-economic.
Vanoutrive, T., Van de Vijver, E., Van Malderen, L., Jourquin, B., Thomas, I., Verhetsel, A., Witlox, F., 2012. What determines carpooling to workplaces in Belgium: location, organisation, or promotion. Journal of Transport Geography. 22 (1), 77–86.
Viegas, J., Martinez, L., Crist, P., 2016. Shared Mobility: Innovation for Liveable Cities. International Transport Forum Corporate Partnership Board.
Wardman, M., Chintakayala, V.P.K., Jong, G., 2016. Values of travel time in Europe: Review and meta-analysis. Transportation Research Part A: Policy and Practice 94 (2016), 93–111.
World Economic Forum (WEF) and Boston Consulting Group (BCG) (2018). "Reshaping Urban Mobility with Autonomous Vehicles - Lessons from the City of Boston," System Initiative on Shaping the Future of Mobility, World Economic Forum, 2018.
Zamparini, L., Reggiani, A., 2007. Meta-analysis and the value of travel time savings: A transatlantic perspective in passenger transport. Networks Spat. Econ. 7, 377–396.