# If Pooling with a Discount were Available for the Last Solo-Ridehailing Trip, How Much Additional Travel Time Would Users Have Accepted and for Which Types of Trips?

January 2024

A Research Report from the National Center for Sustainable Transportation


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**16. Abstract**

Pooled trips in private vehicles, or pooling, can lead to smaller environmental impacts and more efficient use of the limited roadway capacity, especially during peak hours. However, pooling has not been well adopted in part because of difficulties in coordinating schedules among various travelers and the lack of flexibility to changes in schedules and locations. In the meantime, ridehailing (RH) provides pooled services at a discounted fare (compared to the single-travel-party option) via advanced information and communication technology. This study examines individuals' preferences for/against pooled RH services using information collected among travelers answering a set of questions related to their last RH trip. In doing so, both trip attributes and rider characteristics are considered. Taste heterogeneity is modeled in a way that assumes the presence of unobserved groups (i.e., latent classes), each with unique preferences, in a given sample of RH riders (N=1,190) recruited in four metropolitan regions in Southern U.S. cities from June 2019 to March 2020. The researchers find two latent classes with qualitatively different preferences, choosy poolers and non-selective poolers, regarding their choice in favor of/against pooling based on wait time, travel costs, purpose, and travel party size of the last RH trip. Personal characteristics are also identified, specifically age and three attitudes (travel satisfaction, environmentalism, and travel multitasking), which account for individuals' class membership. This research contributes to the literature by explicitly modeling taste heterogeneity towards pooled ridehailing. In addition, unlike existing studies either at the person level or employing stated-preference data, a trip-level analysis is performed in connection with revealed preferences, which generates more realistic and relevant implications to policy and practice.


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## Disclaimer



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A National Center for Sustainable Transportation Research Report

January 2024

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## EXECUTIVE SUMMARY

Pooled trips in private vehicles, or pooling, help reduce environmental impacts and use the limited roadway capacity more efficiently, especially during peak hours. However, pooling has not been very popular in the United States, in part because of preference for privacy and challenge in handling unexpected changes in schedules or locations. In this context, pooled ridehailing (RH) enables unknown travelers with similar schedules and routes to pool rides and save costs, via real-time matching of their ride requests. Still, even with clear monetary incentives and environmental benefits, the proportion of the pooled ride request is only around 20% in the densest cities in the United States, New York, Chicago, and Los Angeles, calling for a deeper understanding of perception, preference, and travel behavior around the adoption of pooled rides, which would inform of effective policies that promote pooling.

Studies have investigated factors behind the adoption and/or frequency of RH in general; however, most of them did not separately study single-party and pooled RH, and even when those that did so did not consider the reasons that might encourage which type of customers to switch, under which conditions, from the “regular” RH to its pooled service. In this context, we pursue a better understanding of factors (e.g., trip attributes and rider characteristics) accounting for the adoption of pooled RH services. In doing so, we improve the realism of stated-preference questions by linking them with respondents’ actual RH trips, and we consider taste heterogeneity in a sample of RH users.

In this research we employ a dataset collected via a transportation survey in four metropolitan areas in the U.S. South between June 2019 and March 2020 with a focus on new mobility services and technology (N=3,365). In the survey, only those who had used single-party RH in the past (N=1,190) were asked to report some trip attributes of their last single-party RH trip, and they were also asked for their maximum additional waiting time for a hypothetical “pooled” trip for their actually taken trip, in exchange of the 50% fare discount. Respondents selected one among five options: No, 1-5 minutes, 6-10 minutes, 11-15 minutes, and 16 minutes or longer. Using this information, we estimate a latent-class ordinal logit model that considers the ordered nature of the outcome variable while assuming unobserved preference heterogeneity among the sample.

We find two classes with taste heterogeneity: choosy poolers (23.6%) and non-selective poolers (76.4%). Choosy poolers’ willingness to accept pooled RH decreases as wait time/travel costs increase. Although counterintuitive, longer wait time and higher RH charges may indicate unique characteristics of their last RH trip, which the survey did not capture fully. For instance,

for the last RH trip, respondents may have preferred privacy, or their trip origins might have been at less crowded areas (e.g., less-dense suburbs, instead of highly dense urban cores) where respondents may be concerned about safety in relation to unknown passengers. As for the trip purpose, choosy poolers are more willing to pool for work/school-related trips than for trips for all the other purposes. Note that many of work/school-related trips take place during daytime or along the major transportation corridor, which are less likely to generate safety issues in relation to unknown passengers. As for the traveling party size, choosy poolers are less willing to accept additional travel time via a pooled ride for trips when they travel with only one known passenger. That is, choosy poolers may want privacy more for such trips than when travelling alone.

Non-selective poolers are willing to accept longer additional travel time, as they waited longer or paid more for their last RH trip. These patterns suggest their high cost-sensitivity or more tolerance towards in-vehicle travel time, likely because of their productive/meaningful use of travel time or low opportunity costs for travel time. As for the trip purpose, non-selective poolers are the most willing to accept a pooled ride for trips to airports, and more willing to do so for return-home, social, other, and shopping trips than for work/school-related ones.

As for the member profile of two classes, older adults are more likely to belong to the choosy pooler than young adults, likely because the latter tend to be technologically savvier or more familiar with (or open to) new types of mobility services. In addition, those with less satisfaction with the current travel patterns, those who are more pro-environment, and those who prefer travel-based multitasking are more likely to be among the non-selective pooler.

This research extends the current knowledge on the factors affecting pooled RH trips, by presenting patterns consistent to those reported in recent studies and those that are not/less examined in the literature. To be specific, environmentalism and travel-based multitasking are associated with willingness to adopt pooled RH, consistent with findings in recent studies. Surprisingly, tech-savviness is found not significant in affecting individuals' pooling decision, likely because all individuals in the analysis are RH users (i.e., technically savvier than non-users) and technical knowledge on how to request for pooling does not necessarily equate to individuals' willingness to do so. Travel satisfaction, which has not been linked to RH research, is found significant in leading to more/less pooling. After all, travelers attempt to improve travel experience, and those not satisfied with their current travel may as well view pooling as a means to do so.

Based on key findings and implications, we recommend the following policies to increase the share of pooled RH. First, for choosy poolers, who would travel with unknown passengers the most for work/school-related trips, running large-capacity vehicles along major transportation corridors during the morning/evening peak hours would be effective. Second, better in-vehicle environments for travel multitasking will be effective in attracting those who prefer productive/meaningful use of travel times to pool instead of travel alone. Third, education campaigns that aim to increase the awareness of environmental impacts of low-occupancy vehicle trips would lead RH users to adopt the preferences of non-selective poolers, instead of those of choosy poolers.

# 1. Introduction

Pooled trips in private vehicles, or pooling, can lead to smaller environmental impacts and more efficient use of the limited roadway capacity, especially during peak hours. From the perspective of infrastructure systems, increasing pooling – all else equal – can be beneficial to society through leading to lower gasoline consumption, reduced GHG emissions and air pollution, and lower traffic congestion levels. In contrast, from the passengers' point of view, pooling may not appear very attractive to many in part because it is not flexible enough to adapt to changes in schedules and locations, and it does not allow privacy. In the U.S., pooling has been historically unpopular, and the share of commute trips made with this means of travel has continuously dropped from above 20 percent in the 1970s to below 10 percent in recent years (Sperling & Brown, Austin, 2019).

Ridehailing is a popular form of shared mobility that has increased flexibility in the choice of the means of travel, while it has also been criticized for its impacts on vehicle miles traveled, including due to deadheading miles it generates for serving passengers (Henao & Marshall, 2019; Schaller, 2017). Ridehailing refers to on-demand door-to-door transportation services requested and paid through smartphone apps. It has proliferated around the world since its first introduction to the urban transportation market in 2012. Ridehailing has the potential for increasing pooling on congested urban streets. With advanced information and communication technology (ICT), ridehailing companies such as Uber and Lyft in the U.S. market made real-time pooling of multiple passengers who share similar routes technically feasible and fare-wise attractive, with additional travel times for multiple pickups and drop-offs. However, the share of "pooled ridehailing" is smaller than one might hope, with only 22-23 percent of the total ridehailing trips in the densest and most populous city in the U.S., New York City, successfully matched and pooled in pre-pandemic conditions (Schaller, 2018). The service was later entirely suspended after the beginning of the COVID-19 pandemic, due to health concerns associated with sharing a vehicle with strangers and the need for social distancing.

Increasing pooling is critical to sustainable transportation not only for today but also for the future in which autonomous vehicles (AV) become available and affordable. AVs are expected to lower the average vehicle occupancy on streets because of their ability to be operated without a driver, or even without passengers at all (as zero-occupancy vehicles, or ZOVs). In response, researchers have investigated the willingness to share AVs under various circumstances, mostly with data collected through stated preference (SP) questions. However, similar studies with a focus on pooled ridehailing, which we believe, are more realistic and linked to actual behaviors of the moment, are relatively limited. In result, there is to date a limited understanding of the user attributes and trip characteristics of pooled ridehailing and their impacts on the willingness to accept a pooled ride under various circumstances.

Many studies have investigated factors behind the adoption and/or frequency of ridehailing in general (Alemi, Circella, Handy, et al., 2018; Alemi, Circella, & Sperling, 2018; Alemi et al., 2019; Conway et al., 2018; Dias et al., 2017; Gehrke et al., 2019; Grahn et al., 2020; Rayle et al., 2016; Sikder, 2019; Young & Farber, 2019). However, most of them did not separately study single-party and pooled ridehailing, and even when those that did so did not consider the reasons that might encourage certain customers to switch, under certain conditions, from the regular form of ridehailing to pooled ridehailing (Malik et al., 2022). In addition, existing studies about willingness to pool RH often employ SP questions under hypothetical scenarios, which control for limited trip attributes and whose answers are likely less reliable than those of revealed preferences (RP).

In this context, we pursue a better understanding of factors accounting for the adoption of pooled RH services, both trip attributes and rider characteristics. In doing so, we improve the realism of SP questions in hypothetical scenarios and consider taste heterogeneity in a sample of RH users recruited from four metropolitan areas in the U.S. South for June 2019-March 2020, before the COVID-19 pandemic in the U.S.

We organize this research report as follows. Section 2 presents the summary of key findings in existing studies and important research gaps. In Section 3, we introduce the main data and the analytical method used for this study, and in Section 4 we discuss results in great detail. In Section 5, we further explore the implications of main findings, and in Section 6, we conclude with key contributions to the literature and practice and limitations and future research directions.

# 2. Literature Review

## 2.1. Factors for the pooling/sharing of ridehailing

In this section, we summarize key findings and limitations of existing studies related to the adoption of pooled RH services, which allow us to identify important research gaps in the relevant literature.

(Hou et al., 2020) examine factors accounting for pool requests among 39 million RH trips (both single-party and pooled combined) in the Chicago metropolitan area from November 2018 to March 2019. In doing so, they begin by computing the proportion of pool requests among those RH trips for given origin and destination pairs (at the census tract level), separately for each of 15-minute time bins throughout the day. With the proportion as the dependent variable, they identify tract-level characteristics and trip-level attributes, statistically associated with the dependent variable. Among tract-level characteristics are median income, population and job density, and airport status at pickup and drop-off neighborhoods. RH trips to/from wealthy/dense neighborhoods and the O'Hare airport (occupying almost an entire census tract) tend to have low rates of pool requests. In addition, among trip-level attributes are time of day, day of week, % fare discount by pooling, and trip distance and duration. Longer RH trips with higher discount rates, especially during the morning peak hours from 5 to 9 AM, tend to have higher pool-request rates than other trips.

While informative with rich details, this study has a few critical limitations. First, it does not control for sociodemographic features of origin/destination census tracts (e.g., % young adults, college graduates, and racial majority), leading to the overestimation of the effects of included variables, income and density. Note that the RH literature consistently presents that users' sociodemographics explain their pooling decision. Second, its unit of analysis is the OD pair for a specific time bin, which puts higher weights on those OD pairs with fewer RH trips (e.g., intra-suburbs) and lower weights on those OD pairs with more RH trips (intra-urban), as long as the number of RH trips are considered. This is among the reasons for which its results are counter-intuitive: e.g., trips to/from high-density tracts are associated with low rates of pool requests. Third, it models "average" effects of neighborhood features and trip attributes in the sample, while not explicitly modeling potential heterogeneous preferences for pooling across neighborhoods (and across travelers).

Lavieri and Bhat (2019b) investigate complex relationships around four choice outcomes – residential location, vehicle availability, RH experience, and RH frequency – with a survey data (N=1,607 commuters) collected in fall 2017 in the Dallas-Fort Worth Metropolitan Area. While modeling the four outcomes in a single framework, generalized heterogeneous data model (GHDM), they test statistical associations of these outcomes with individual/household characteristics and especially four attitudinal factors, privacy sensitivity, technology savviness, variety seeking lifestyle propensity, and green lifestyle propensity. They find that those who are more sensitive regarding privacy, technologically savvier, and seeking more variety are more likely to have used pooled RH in the past, than having not used RH at all, compared to those who are less so. In addition, those who belong to racial/ethnic minorities, earn a graduate degree, with high household incomes, live in cities/suburbs, and with more than one vehicle per household worker tend to have had passengers matched via apps on their RH trips, compared to those who do not. While this study makes critical contributions to the literature, it presents an individual-level analysis, which does not allow to further examine the reasons why the same individuals choose single-party or pooled RH, depending on trip attributes.

Tirachini and del Rio (2019) determine factors accounting for vehicle occupancy rates with survey data collected on working days from November 14$^{th}$, 2017 to December 5$^{th}$, 2017 in Santiago, Chile. As for the recruitment of the survey, they approach (i.e., intercept) ridehailing passengers on streets, who just finished their trips at 64 spots across the region, randomly selected among 412 spots with high-attraction potentials, identified with a recent origin destination survey of the region. Their model results present that leisure trips by those with low household incomes tend to have high vehicle occupancy, compared to others. Although the study includes valuable insights into pooled RH practices in a developing country, it does not clearly define vehicle occupancy rates, either/both pooling with others in the same travel party or those matched via RH apps. Since these two types of pooling present very different implications to travel cost, time, and expected environmental benefits, this study provides a limited understanding of pooling behaviors. In addition, key trip attributes such as travel time and costs were not tested in the modeling stage, possibly because of lack of data.

Alonso-Gonzalez and her colleagues (2020) present one of very few examples in the literature, explicitly modeling heterogeneous preferences for/against pooled RH. They employ stated preference (SP) survey data, collected from those households in the Netherlands Mobility Panel in May 2018 (N=1,006). After all, pooled RH services were not available in the market at the time of data collection, so SP was inevitable. Still, to have respondents' answers to hypothetical choice scenarios to be more reliable, they linked the levels of three attributes (travel time, travel costs, and additional passengers matched by RH apps) to actual trips that respondents reported earlier in the survey. Their latent-class choice model allows to identify four unobserved groups. Members of these groups value travel time, costs, and privacy homogenously within the same group, but heterogeneously across different groups. For instance, the “It’s my ride” class (29%) are willing to pay the most to avoid pooling, the “Time is gold” class (24%) report the highest value of time, and the “Cheap and half empty, please” class (19%) hold the lowest value of time. Interestingly, they find the “Sharing is saving” class (28%), who are the least willing to avoid pooling (i.e., the most willing to accept pooled RH) among the four classes. While informative, their membership model includes quite a limited set of covariates regarding individual, household, built environment, and attitudinal traits. Thus, their study does not help us very much when understanding underlying choice-making processes and developing tailored approaches to target subgroups for the promotion of pooled RH services.

Kang and her colleagues (2021) estimate joint revealed- preference and stated-preference models to better understand the value of travel time and privacy (i.e., traveling alone instead of pooling with strangers by RH apps) among residents (N=953) recruited to a survey in Austin, TX in fall 2019. The joint model includes five choice outcomes, (1) familiarity with pooled RH (ordinal scale converted to binary), (2) choice for the last trip by RH (either single-party or pooled services), and (3) answers to three SP questions, each with two options (either single-party or pooled services) that varies by three attributes (travel time, travel costs, and number of additional passengers). When estimating an integrated choice and latent variable model, they also test if three attitudinal factors account for these choice outcomes, tech-savviness, sharing propensity, and green lifestyle propensity. Interestingly, tech-savviness is found to be *negatively* associated with pooled RH, both for past experience and choices under hypothetical scenarios. That is, respondents of the survey chose single-party services, not because they were not capable of requesting for pooled services. Instead, the association between tech-savviness and single-party services appears to be related to their modeling setup, which allows income to account for one’s tech-savviness. In their model, these two are positively associated: i.e., either tech-savvy individuals tend to be more productive or wealthier individuals have more opportunities to interact with ICT devices and services. Thus, tech-savvy travelers may belong to households with high incomes, who on average hold high value of time and are willing to pay to avoid pooling (more than lower-income counterparts). By contrast, sharing propensity and green lifestyle propensity are positively associated with most choice outcomes. In the meantime, more educated individuals tend to choose pooled services for their last RH trip, and those living in high-density neighborhoods do so too likely because of a higher chance of getting pooled, but additional travel times not likely very much.

Lavieri and Bhat (2019a) investigate factors underlying the current RH experience and future RH choices in AVs of 1,607 commuters, recruited in the Dallas-Fort Worth Metropolitan Area, TX in fall 2018 (the same data as those in their early study (Lavieri & Bhat, 2019b)). In doing so, they employ an integrated choice and latent variable model to account for three choice outcomes, the current RH experience (multinomial: no, private only, and pooled) and choices under hypothetical scenarios with RH AVs (binary: private or pooled RH in AVs). For the latter questions, respondents were asked two questions (one for work and the other for a leisure purpose) with various levels in time, costs, and additional passengers matched via RH apps. In their model, privacy-sensitivity is negatively associated with three choices, the current pooled RH experience and two choices about future pooled RH in AVs, and interest in productive use of travel time is positively associated with two of the current RH experiences, both private-only and pooled with strangers.

While methodologically rigorous and data-wise rich and thorough, their results appear to be inconsistent internally across choice outcomes and externally with common expectations. For instance, urban residents tend to have experienced pooled RH in the past; however, they would choose pooled RH less than their suburban/rural counterparts in AVs in a future. Likewise, those in vehicle-sufficient households (i.e., more than one vehicle per household worker) are more likely to have used pooled RH before, but less likely to select pooled RH (than private RH) in AVs for a commute purpose. One reason behind these inconsistencies may be related to a few dimensions of their SP questions working in complex ways: e.g., trip purpose and the presence of a human driver inside the RH vehicle. In this context, their limited scenarios do not allow them to examine the complex nature of current and future choices under various circumstances. In addition, attributes of trips for the same purpose could be varied widely, and all (or most) critical factors that respondents considered may not have been observed and controlled for in their data collection and analysis.

Bansal and his colleagues (2016) examine factors accounting for the adoption of RH services in AVs under three hypothetical pricing scenarios with stated-preference survey data, collected in Austin, TX (N=347) in October-December 2014. In the survey, respondents were asked to select preferred frequency levels for such services in a future with AVs: rely less than once a month, rely at least once a month, relay at least once a week, and relay entirely on shared autonomous vehicle (SAV) fleet. Their three models, one for each price point, present that various household, individual, and built-environment attributes, attitudes, and mobility-related choices account for the adoption of RH in AVs. Note, however, that these stated-preference questions did not ask respondents to choose among distinct means of transportation (e.g., pooled vs. single-party RH). In other words, the survey captured respondents' willingness to adopt *asynchronous* AV-sharing services on its own, but it did not explicitly remind respondents to consider trade-offs between the use of these new services and other conventional travel modes. In addition, their univariate models do not allow to separate out the effects of using other travel modes more or less in an AV future.

When investigating factors behind the adoption of (hypothetical) pooled RH services in AVs, Krueger and his colleagues (2016) considered trip attributes more than those in other studies. When designing stated-preference choice experiments, their survey first collected detailed trip attributes for a trip that respondents actually took (i.e., the reference trip): e.g., purpose, in-vehicle travel time, wait time, travel costs, and addresses for the origin and destination. Then, each of the five SP questions in a following section asked respondents to select the most preferred travel mode for the same travel context (as that of the reference trip) among three options, two hypothetical alternatives and the chosen mode. These hypothetical modes are solo and pooled RH in AVs with various levels of in-vehicle travel time, wait time, and travel costs. Interestingly, when deciding the attribute levels of the two hypothetical alternatives, the authors considered (i.e., pivoted) those of the reference trip for the improvement of the realism of choice scenarios. Their results indicate that age, the travel mode and purpose for the reference trip, modality, and carsharing-user status account for the adoption of pooled RH in AVs, but not the other individual/household characteristics (e.g., gender, income, presence of a child in the household, and car availability). The unique contributions of this study include its estimation of effects of *more* trip attributes than travel time and costs. Still, it is not clear whether and to what extend these effects differ for human-driven RH services, which are in operation in most cities at the moment and immediately demand effective policy and regulations.

While informative and insightful, existing studies leave a few important research gaps, which we attempt to fill in this research. First, studies employ pure SP questions, which tend to control for a limited number of trip attributes because of response burdens and whose answers are likely less reliable than those to revealed preference (RP) questions, or questions about their actual choice. Second, studies examine individuals' past/future choice of pooling at the individual level, but not at the trip level. However, given that the same individuals could change their choice depending on specific travel contexts, individual-level analyses provide limited understanding of factors and processes related to the adoption of pooled rides. Third, studies investigate the adoption of pooled rides inside AVs (i.e., without a human driver in the vehicle). Their authors discuss important implications to infrastructure management in the future; however, it is not clear whether and to what extent individuals would accept pooling differently in a human-driven vehicle versus machined-driven one. Note that the former has direct implications to planning and policy of the moment, while the latter may be situated in complex relationships and with diverse factors, not all of which have been identified, measured, or examined. Last but most importantly, most studies do not consider taste heterogeneity; however, it is quite plausible that individuals hold unique preferences regarding in what travel contexts they would accept traveling with unknown passengers more/less.

**Table 1. Studies on factors accounting for pooled ridehailing**

| Study | RP | SP (for each R) | Study area, data collection period, recruitment, & sample size (N) | Analytical methods | TB (outcome) | SED | BE | Attitudes | TB (control) | Trip attributes |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Trips | - | Chicago Metropolitan Area, 11/2018-03/2019, trip data submitted by TNCs and shared by the city, N=39 million (trips) | Ordinary least square & extreme gradient boosting | Share of pool requests among RH trips in given OD pairs and time bins | Median income (-) at OD census tracts | Population density (-), job density (-), airport status (-) at OD census tracts | - | - | Time of day, day of week, % fare discount by pooling (+), distance (+), duration (+) |
| 2 | Overall use | - | Dallas-Fort Worth Metropolitan Area, fall 2017, convenience sample via mailing lists, N=1,607 | Generalized heterogeneous data model | Residential location (multinomial), vehicle availability (ordinal), RH experience (multinomial), & RH frequency (ordinal) | Age (+), NH-White (-), education (+), income (+), HH composition (single-worker multi person – than other HH types) | Live in urban or suburban compared to rural (+) | Privacy sensitivity (-), tech-savviness (+), variety seeking lifestyle propensity (+) | Vehicle per HH worker (+) | - |
| 3 | Last trip | - | Santiago, Chile, working days from Nov 14, 2017-Dec 5, 2017, intercept surveys, N=1,529 | Generalized ordered logit | Vehicle occupancy rates (passengers per RH vehicle) | Income (-) | - | - | - | Purpose (leisure, +) |
| 4 | - | Four questions | Urban areas in the Netherlands, recruited from the household panel of the Netherlands Mobility Panel (MPN), May 2018; N=1,006 | Mixed logit & latent-class choice model | Solo vs. pooled RH | Employment, income, age | - | - | Never used BTM (bus, tram, metro) before | In-vehicle time, cost, & number of additional passengers |

| Study | RP | SP (for each R) | Study area, data collection period, recruitment, & sample size (N) | Analytical methods | TB (outcome) | SED | BE | Attitudes | TB (control) | Trip attributes |
|---|---|---|---|---|---|---|---|---|---|---|
| 5 | Last trip | Three questions | Austin, TX; convenient sample via purchased email list, SNS ads, & professional networks; fall 2019; N=953 | Generalized heterogeneous data model | Familiarity, type of the last RH trip, solo/shared RH for three scenarios | Gender, age, race, education (+), tenure, employment (+), income (-) | Urban/suburban (vs. rural), transit access (binary), pop density (+, high vs. not high), | Tech-savviness (-), sharing propensity (+), green lifestyle propensity (+) | - | Trip purpose, time, cost, & number of additional passengers |
| 6 | Overall use | Two questions | Dallas-Fort Worth Metropolitan Area, fall 2017, convenience sample via mailing lists, N=1,607 | Generalized heterogeneous data model | Current experience (multinomial: no, private only, or pooled), choices for RH in AVs (binary: private vs. pooled for a work trip and for a leisure trip, separately) | Gender (male, +), age, race, education (-), employment, income, household composition | Residential neighborhood (urban vs. non-urban), | Privacy-sensitivity (-), time-sensitivity (-), interest in productive use of travel time (IPTT) (+) | Vehicle availability, commute mode | Time, cost, & number of additional passengers |
| 7 | - | Three questions | Austin, TX; Oct-Dec, 2014; recruited through neighborhood associations; N=347 | Ordered probit | For three cost scenarios ($1, $2, and $3/mile), ordered response on expected frequency - four levels from rely less than once a month up to rely entirely on SAV fleet (asynchronous sharing) | Household size (+), male (+), number of children (-), full-time employment (+), age (-), | Distance from workplace (+), population density (+), household density (-), employment density (-), service employment density (-) (at traffic analysis zone at home) | Have heard about the Google car before (+), "Anti-lock braking system (ABS) is a form of automation." (+), familiar with carsharing (-) | Driver's license (-), annual vehicle miles traveled (VMT) (-) | Each scenario has distinct travel costs ($1, $2, and $3/mile) |
| 8 | - | Five questions | Major metropolitan areas of Australia (Adelaide, Brisbane, Melbourne, Perth, & Sydney); April 2015; online opinion panel; N=435 | Mixed logit | Most preferred mode among three options: solo and pooled RH in AVs, and the chosen mode (for the reference trip) | Age (-) | - | - | Modality, car sharing user (+) | Trip purpose & means of transportation (for the reference trip), in-vehicle time, waiting time, & cost |

*Notes*: 1: Hou et al. (2020), 2: Lavieri & Bhat (2019b), 3: Tirachini and Rio (2019), 4: Alonso-Gonzalez et al (2020), 5: Kang et al (2021), 6. Lavieri and Bhat (2019a), 7: Bansal, Kockelman, and Singh (2016), 8: Krueger, Rashidi, and Rose (2016)

# 3. Data & Methods

## 3.1. Data & Variables

In this research, we employ rich survey data, collected from July 2019 to March 2020 (before the COVID-19 pandemic started in the U.S.) in four regions of the southern United States, Phoenix, AZ, Atlanta, GA, Tampa, FL, and Austin, TX. Since 2017, researchers in four institutions, Arizona State University, the Georgia Institute of Technology, the University of South Florida, and the University of Texas at Austin, have collaborated on a survey design and data collection project. The project focuses on the current use patterns, attitudes, and future envisioned adoption of emerging mobility services and autonomous vehicles. With almost identical survey instruments, each institution administered the survey in their own region by mailing and emailing residents or running online ads on a social network service, Facebook. The survey collected rich information on the following topics from more than 1,000 respondents in each of the Phoenix, Atlanta, and Austin regions, with additional 260 cases in the Tampa region. Topics asked in the survey are: “Attitudes and Preferences”, “Household Vehicles and Residential Preferences”, “Current Travel Patterns”, “Mobility on Demand”, “Your Thoughts on Autonomous Vehicles”, and “Background Information”.

The U.S. Department of Transportation (DOT) funded survey design and data collection efforts through its University Transportation Center (UTC) program. To be specific, TOMNET (Teaching Old Model NEw Tricks), a Tier-1 UTC, supported researchers at three institutions, and those at the University of Texas at Austin received funding through a different UTC.

In this research, we analyze responses in the Mobility on Demand section, which asked about the adoption, frequency, and perceptions of shared mobility services, such as ridehailing, carsharing, bikesharing, and e-scooter sharing. We particularly focus on the specific details of the last trip made by ridehailing, which were asked only to ridehailing users. These details include its type (single-party or pooled RH), origin/destination, time of a day, wait time, travel time, trip costs, purpose, travel party, alternative means of travel if ridehailing had not been available, and the maximum additional travel time to accept a pooled ride if it had been available with a 50% discount in the fare.

From the entire sample (N=3,365) of the survey data, we form a subsample (n=1,190) that includes those who made a single-party ridehailing trip recently and answered related questions properly (i.e., cases without missing on key variables). Table 2 presents summary statistics of trip attributes and user characteristics for the subsample for two latent classes separately (more details follow in the Results section).

## Table 2. Summary statistics of the study sample and latent classes (weighted by class probabilities)

| Trip attributes | Choosy pooler (23.6%) | Unselective pooler (76.4%) | Sample (N=1,190) | Rider characteristics | Choosy pooler (23.6%) | Unselective pooler (76.4%) | Sample (N=1,190) |
|---|---|---|---|---|---|---|---|
| Maximum acceptable additional travel time | | | | Age group | | | |
| No | 89.32% | 13.91% | 31.68% | 18-24 | 6.54% | 23.16% | 19.24% |
| 1-5 min | 6.33% | 20.70% | 17.31% | 25-34 | 18.14% | 17.05% | 17.31% |
| 6-10 min | 4.35% | 33.95% | 26.97% | 35-44 | 17.63% | 13.37% | 14.37% |
| 11-15 min | 0.00% | 21.99% | 16.81% | 45-64 | 37.71% | 34.00% | 34.87% |
| 16+ min | 0.00% | 9.46% | 7.23% | 65+ | 19.98% | 12.42% | 14.20% |
| Time of the trip | | | | Sex | | | |
| Weekday daytime | 52.77% | 48.37% | 49.41% | Female | 52.00% | 57.00% | 56.00% |
| Weeknight[1] | 14.61% | 15.95% | 15.63% | Race | | | |
| Weekend daytime | 9.82% | 9.95% | 9.92% | White or Caucasian | 80.17% | 74.34% | 75.71% |
| Weekend night[2] | 22.80% | 25.73% | 25.04% | African American | 7.90% | 8.89% | 8.66% |
| Travel costs | | | | Native American | 0.36% | 0.66% | 0.59% |
| *ln*(wait time+1) | 1.95 | 1.94 | 1.94 | Asian/Pacific Islander | 6.36% | 10.46% | 9.50% |
| *ln*(travel costs+ 1) | 2.97 | 2.87 | 2.90 | Other | 5.20% | 5.65% | 5.55% |
| Size of traveling party except the respondent | | | | Educational attainment | | | |
| None (alone) | 51.33% | 53.33% | 52.86% | Up to high school | 2.86% | 7.59% | 6.47% |
| One | 23.42% | 22.35% | 22.61% | Some college | 24.20% | 26.51% | 25.97% |
| Two | 10.34% | 8.36% | 8.82% | Bachelor | 39.88% | 38.72% | 38.99% |
| Three or more | 9.59% | 8.48% | 8.74% | Graduate | 33.06% | 27.19% | 28.57% |
| missing | 5.32% | 7.49% | 6.97% | Work/study status | | | |
| Trip purpose | | | | Worker | 74% | 73% | 73% |
| Work/school | 14.99% | 15.17% | 15.13% | Student | 12% | 24% | 21% |
| Shopping | 5.67% | 7.27% | 6.89% | Annual household income before taxes (as of July 19-March 20) | | | |
| Social | 34.27% | 37.37% | 36.64% | Less than $50,000 | 16.27% | 24.01% | 22.18% |
| Airport | 23.81% | 19.05% | 20.17% | $50,000 to $99,999 | 26.41% | 29.24% | 28.57% |
| Transit | 1.63% | 1.26% | 1.34% | $100,000 or more | 57.32% | 46.75% | 49.24% |
| Return home | 12.91% | 15.04% | 14.54% | Household vehicle | | | |
| Other | 6.72% | 4.85% | 5.29% | No car | 2.44% | 5.08% | 4.45% |
| Alternative mode if RH services had not been available | | | | One car | 22.42% | 24.42% | 23.95% |
| Drive alone | 20.38% | 19.55% | 19.75% | Two cars | 44.03% | 39.20% | 40.34% |
| Drive with others | 19.74% | 16.89% | 17.56% | Three or more cars | 31.11% | 31.31% | 31.26% |
| Get a ride | 9.01% | 11.85% | 11.18% | Attitudes[3] | | | |
| Ride a bus | 5.07% | 8.55% | 7.73% | Travel satisfaction | 0.12 | -0.14 | -0.08 |
| Ride light rail | 4.34% | 2.62% | 3.03% | Tech-savvy | 0.26 | 0.37 | 0.34 |
| Hail a taxi | 25.22% | 21.91% | 22.69% | Environmentalism | -0.22 | 0.12 | 0.04 |
| Shared bike/e-scooter | 0.39% | 1.20% | 1.01% | Pro TOD | 0.01 | 0.20 | 0.16 |
| personal bike/scooter | 0.47% | 0.40% | 0.42% | Pro multitasking | 0.01 | 0.21 | 0.16 |
| Walk | 3.80% | 4.21% | 4.12% | Unitasking | -0.17 | -0.09 | -0.11 |
| Cancel the trip | 5.86% | 8.20% | 7.65% | Pro transit | -0.22 | -0.05 | -0.09 |
| Other | 5.72% | 4.61% | 4.87% | Pro control | 0.07 | -0.10 | -0.06 |
| | | | | Metropolitan area | | | |
| | | | | Phoenix, AZ | 31.14% | 26.68% | 27.73% |
| | | | | Atlanta, GA | 34.45% | 28.96% | 30.25% |
| | | | | Tampa, FL | 7.96% | 7.11% | 7.31% |
| | | | | Austin, TX | 26.45% | 37.25% | 34.71% |

*Notes*: 1. Excluding Friday night, 2. Including Friday night, 3. For attitudinal statements and factor loadings, refer to Table 5.

## 3.2. Latent-class choice model (LCCM)

We employ the latent-class choice model (LCCM), which captures heterogeneous preferences in a sample. LCCM assumes the existence of unobserved groups (i.e., latent classes), whose preferences for/against the outcome of interest (in this research, how long to travel more for a pooled ride with a fare discount) are homogeneous within the same group but heterogeneous across groups. Since the group membership of individuals is not known to researchers and to individuals themselves, LCCM estimates the probabilities of individuals belonging to one class or another via the membership model, while simultaneously modeling the choice of interest via class-specific choice models.

We find LCCM very effective for the identification of heterogeneous influences of various factors on the willingness to accept pooled rides for the following reasons. First, ridehailing users are diverse regarding personal attributes such as socioeconomics, demographics, attitudes, perceived benefits and drawbacks of ridehailing, and previous experience and typical use of shared mobility services and other alternative modes. Second, certain trips are more conducive to pooling while others are not as much. That is, the same user may or may not accept a pooled ride for their last solo-ridehailing trip, depending on its trip characteristics including trip purpose, time of a day, origin/destination, travel party, and available alternative modes. Third, with diverse user characteristics, the responsiveness with which users respond to trip attributes is likely to differ across individuals. For example, members of a group may accept a pooled ride even under seemingly un-favorable travel contexts (i.e., less sensitive to presumably substantial barriers to pooling), while those of another group may be highly reluctant to accept pooling under very favorable situations (i.e., more sensitive to seemingly minor inconvenience and/or discomfort).

Here are details on our modeling setup (Refer to Figure 1). In the membership model, we test personal characteristics to estimate individuals' probabilities of belonging to distinct latent classes. In the choice model, we investigate the effects of trip attributes on users' acceptance of a pooled ride for their last solo-ridehailing trip. The choice of interest is a five-level ordinal response indicating the maximum additional travel time (in minutes) that individuals would have accepted for their last single-party RH trips with the exchange of a 50% fare discount, zero additional minutes (i.e., no pooling), 1-5 additional minutes, 6-10 additional minutes, 11-15 additional minutes, and 16 or more additional minutes.

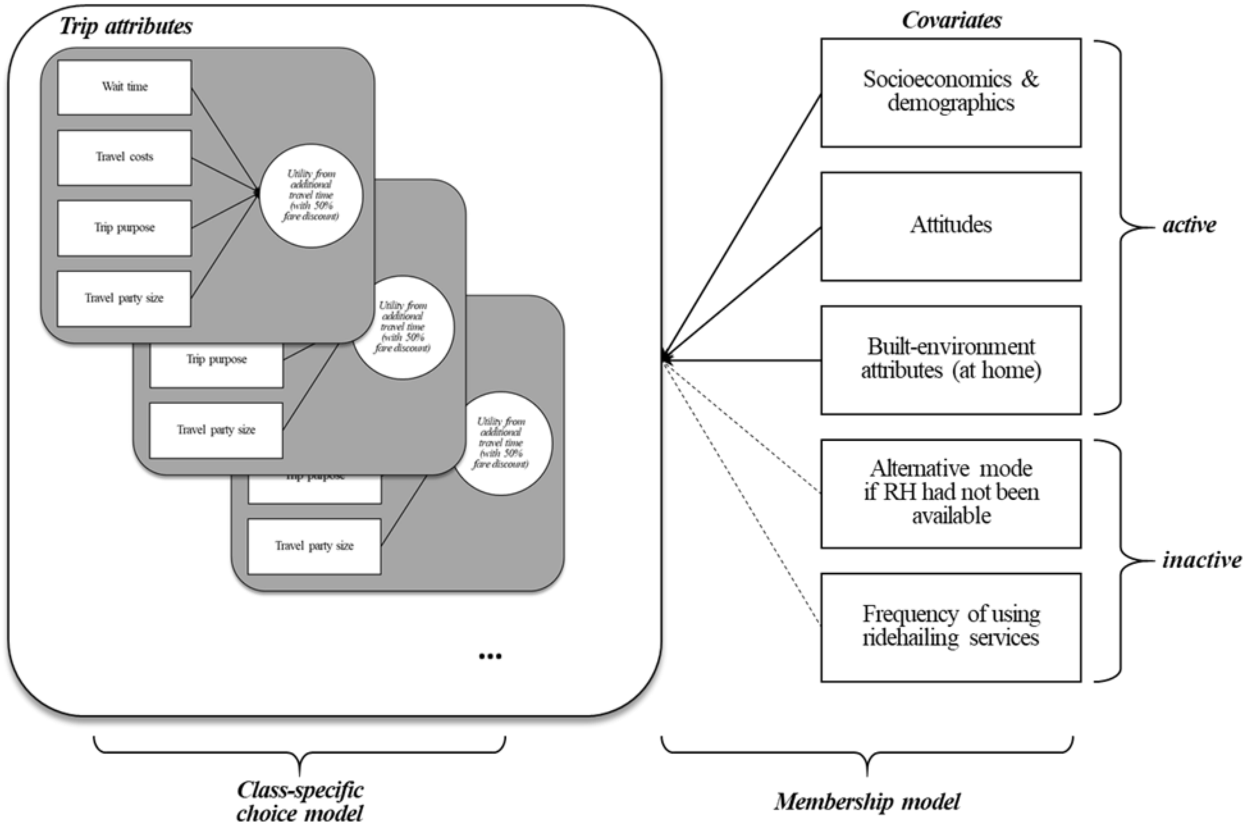


**Figure 1. Conceptual diagram of the latent-class choice model**

# 4. Results

## 4.1. Goodness of fit measures

To determine the most appropriate number of latent classes in the sample, we estimate LCCM in a simple structure (i.e., only with two trip attributes, *ln*(wait time) and *ln*(travel costs), in the choice model, but not covariates in the membership model) with varying numbers of classes from two to five. With LCCM results, we check goodness of fit measures and see if each solution identifies latent classes with distinctive preferences. By employing these two criteria, we choose a two-class solution as the most appropriate, and we further develop LCCM with covariates in its membership model. Table 3 includes goodness of fit measures for latent classes from two to five. Note that models with more than five latent classes generate a class with too few cases, whose preferences appear to be better described as those of outliers.

**Table 3. Goodness-of-fit measures for latent-class choice models (N=1,190)**

| Number of latent classes | Number of free parameters | Log-likelihood | AIC | BIC | Adjusted BIC[1] | Entropy | Size of classes (by descending order) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Class#1 | Class#2 | Class#3 | Class#4 | Class#5 |
| 1 | 6 | -1789.087 | 3590.174 | 3620.664 | 3601.606 | | 1 | | | | |
| 2 | 13 | -1764.102 | 3554.204 | **3620.266** | **3578.973** | 0.534 | 0.61734 | 0.38266 | | | |
| 3 | 20 | -1755.911 | 3551.822 | 3653.456 | 3589.929 | 0.588 | 0.69779 | 0.22200 | 0.08021 | | |
| 4 | 27 | -1744.498 | **3542.996** | 3680.202 | 3594.440 | 0.758 | 0.57353 | 0.28978 | 0.08131 | 0.05538 | |
| 5 | 34 | **-1737.627** | 3543.254 | 3716.032 | 3608.036 | 0.732 | 0.44601 | 0.29301 | 0.11244 | 0.08567 | 0.06287 |

*Notes*: 1. For the sample-size adjusted BIC, n* = (n+2)/24 is used instead of n. **Bolded values** indicate the best performance for each goodness-of-fit measure (i.e., for each column), except entropy, which is not a goodness-of-fit measure.

## 4.2. Choice model

### *4.2.1. Choice outcomes by class*

Figure 2 presents the proportions of five responses by members of two latent classes separately and for the entire study sample together (N=1,190). Note that for the class-specific proportions, individuals' probabilities for the two classes, estimated in the membership model, are used as weights.

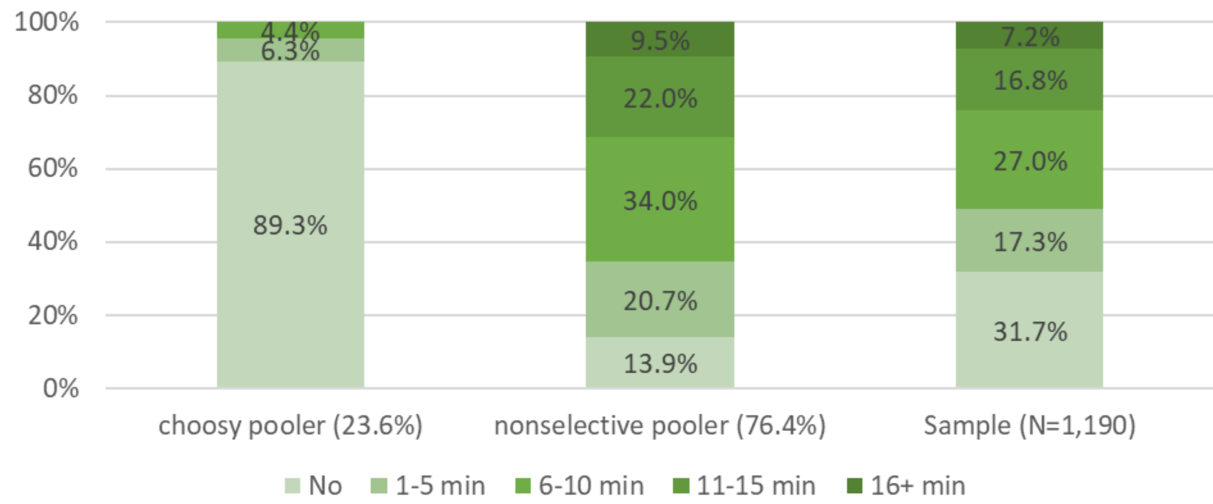


**Figure 2. Selected choices by members of two latent classes and for the entire sample**

The majority of choosy poolers (89.3%) report not being willing to travel any longer for a pooled ride in exchange of the 50%-discounted fare. Among them, only 6.3% are willing to travel longer for 1-5 minutes; 4.4% for 6-10 minutes; and 0% for more than 10 minutes. Members of choosy poolers appear to consider pooling with unknown passengers only for very few, specific occasions. By contrast, the majority (e.g., 86.1% = 100% - 13.9%) of non-selective poolers are willing to spend none-zero additional minutes on their last RH trip if they were given the same discount. The largest proportion is found for additional 6-10 minutes, and next largest proportions are for 11-15 minutes (22.0%) and 1-5 minutes (20.7%). Even one out of every ten non-selective poolers (9.5%) would be willing to sacrifice 16 minutes or longer, in addition to their actual travel time, in exchange for the discounted fare. Non-selective poolers appear to be either highly cost-sensitive or experience less disutility from longer in-vehicle time, compared to choosy poolers. In sum, the members of these two latent classes select their responses to the hypothetical scenario with a deep fare discount, in quite distinctive ways.

### *4.2.2. Preferences of choosy poolers*

Next, we examine the two sets of coefficients in the choice model (see Table 4), one for each class. We do so because these coefficients reveal different preferences for/against pooled RH present in the sample of RH riders, or taste heterogeneity. Note that coefficients allow us to see which factors account for selecting (or not selecting) additional travel time in exchange of the fare discount, and these factors could differ between the two classes in terms of statistical significance, sign, and magnitude.

Choosy poolers' willingness to accept pooled RH decreases as wait time/travel costs increase, which appears counter-intuitive at first glance. Longer wait time and higher RH charges may indicate unique characteristics of their last RH trip, which may have affected their choice (although unfortunately the survey didn't capture fully): among trips with such characteristics are long trips for which respondents want privacy, whose origins are at less crowded areas (e.g., less-dense suburbs, instead of highly dense urban cores) where respondents may be concerned about safety in relation to unknown passengers. Note that the mean wait time and travel costs do not differ much between two classes (see Table 1). In other words, it is *perceived* time/costs that account for riders' willingness for a pooled ride, but not necessarily objectively measured time/costs (although respondents self-reported time/costs for their last RH, which may be inaccurate and biased).

As for the trip purpose, choosy poolers are more willing to pool with unknown travelers for work/school-related trips than for trips for all the other purposes. While work/school-related trips are often time-constrained (e.g., morning commutes), many of them take place during daytime or along the major transportation corridor, which are less likely to generate safety issues in relation to unknown passengers matched via RH apps. By contrast, choosy poolers are the least willing to accept pooled RH for return-home trips, many of which take place during night time or along less-dense local roads, likely because of their preference for privacy/safety.

As for the traveling party size, choosy poolers are less willing to accept additional travel time via a pooled ride for trips when they travel with only one known passenger. That is, choosy poolers may want privacy more for such trips than when travelling alone. By contrast, choosy poolers are more likely to accept longer travel time with the fare discount when they travel with two known passengers (i.e., their travel party has three passengers including themselves). It appears that they may feel more comfortable (less concerned of safety) sharing the vehicle space with the unknown passenger when their own traveling party is large enough.

### *4.2.3. Preferences by non-selective poolers*

Non-selective poolers are willing to accept longer additional travel time in exchange of the 50% fare discount, as they waited longer or paid more for their last RH trip. Note that the average fare for the last RH trip is slightly lower for non-selective poolers than choosy poolers although they are not vastly different. To be specific, on average, non-selective poolers paid \$5 less than choosy poolers did for the last RH trip. Still, non-selective poolers are substantially more likely to accept a pooled RH than choosy poolers when actual fares get more expensive. Again, these patterns may suggest their high cost-sensitivity or more tolerance towards in-vehicle travel time, likely because of their productive or meaningful use of travel time or low opportunity costs in time.

As for the trip purpose, unlike choosy poolers, who are the ***most*** willing to get pooled on work/school-related trips, non-selective poolers are the ***least*** willing to do so on the same type of trips. Instead, non-selective poolers are the most willing to accept a pooled ride for trips to airports, and more willing to do so for return-home, social, other, and shopping trips (by the descending order of the coefficient size) than for work/school-related ones. Especially for trips to airports, many of which are neither short nor cheap on fares (i.e., airports are often quite far from the downtown or suburban neighborhoods), non-selective poolers may be motivated more by cost saving, while choosy poolers may be not as much. After all, choosy poolers may value privacy on such trips (e.g., preparation for a long-distance trip) or be compensated by their employers for their costs, which leaves them little incentives for a fare discount.

When deciding to travel with unknown passengers, non-selective poolers do not appear to consider the travel party size. Statistically speaking, none of the four coefficients are statistically significant in their choice model. That is, once travel costs and purposes are accounted for, we do not see any remaining effects by the travel party size in non-selective poolers' choice of pooling versus non-pooling. This could indicate that as long as RH vehicles can physically accommodate more passengers, non-selective poolers do not mind sharing the vehicle space with unknown passengers, regardless of having their own travel party or not. After all, non-selective poolers may not necessarily link travelling with unknown passengers to their own privacy being violated/compromised, even when they travel with their family, friends, or colleagues.

## 4.3. Membership model

To identify the rider profiles of two latent classes, we test a diverse set of individual/household characteristics and attitudinal factor scores. As a result, we find a few variables that are statistically significant in accounting for individuals' class membership: respondents' age and attitudes.

Those who 25 years old or older are more likely to belong to choosy pooler than non-selective pooler, compared to those who are younger than 25 years old. Four coefficients, each indicating one of the four older adult groups, present similar magnitude with the same positive sign, indicating that among these older adult groups, probabilities of belonging to one or the other class do not differ very much.

Among nine general attitudes, we find three are statistically significant in explaining the class membership of the 1,190 RH riders in the sample, commuter, environmentalism, and pro-multitasking on travel. First, those RH riders with high scores on commuter tend to belong to choosy poolers, compared to non-selective poolers. Second, those with high scores on environmentalism are less likely to belong to choosy poolers (i.e., more likely to non-selective poolers). Third, likewise, those with high scores on pro-multitasking on travel are less likely to be found among choosy poolers (i.e., more likely among non-selective poolers).

### Table 4. Choice and membership model results

| Choice model | choosy pooler (23.6%) | | | | non-selective pooler (76.4%) | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | S.E. | Est./S.E. | P-Value | Estimate | S.E. | Est./S.E. | P-Value |
| Cost | | | | | | | | |
| *ln* (wait time+1) | -444.04 | 9.12 | -48.68 | 0.00 | 0.51 | 0.13 | 4.06 | 0.00 |
| *ln*(travel cost+1) | -531.93 | 14.26 | -37.30 | 0.00 | 0.57 | 0.13 | 4.30 | 0.00 |
| Purpose (ref: work/school-related) | | | | | | | | |
| Shopping | -403.97 | 0.00 | 999.00 | 1.00 | 0.24 | 0.27 | 0.87 | 0.38 |
| Social | -313.34 | 7.34 | -42.70 | 0.00 | 0.61 | 0.21 | 2.88 | 0.00 |
| To airport | -234.80 | 2.17 | -108.46 | 0.00 | 0.90 | 0.24 | 3.71 | 0.00 |
| return home | -845.54 | 17.60 | -48.03 | 0.00 | 0.65 | 0.24 | 2.75 | 0.01 |
| Others | -626.76 | 14.33 | -43.75 | 0.00 | 0.56 | 0.39 | 1.42 | 0.16 |
| Traveling party size, except the respondent (ref: zero) | | | | | | | | |
| One | -94.07 | 1.16 | -81.14 | 0.00 | -0.21 | 0.17 | -1.25 | 0.21 |
| Two | 26.73 | 2.46 | 10.86 | 0.00 | -0.31 | 0.28 | -1.11 | 0.27 |
| Three or more | -371.13 | 0.00 | 999.00 | 1.00 | 0.10 | 0.29 | 0.36 | 0.72 |
| Missing | -683.88 | 0.00 | 999.00 | 1.00 | 0.04 | 0.26 | 0.13 | 0.89 |
| Thresholds | | | | | | | | |
| level 1 | -2269.65 | 53.49 | -42.43 | 0.00 | 1.15 | 0.40 | 2.88 | 0.00 |
| level 2 | -2025.81 | 47.87 | -42.32 | 0.00 | 2.42 | 0.42 | 5.83 | 0.00 |
| level 3 | 4.81 | 0.00 | 999.00 | 1.00 | 3.96 | 0.44 | 9.03 | 0.00 |
| level 4 | 5.48 | 0.00 | 999.00 | 1.00 | 5.53 | 0.47 | 11.87 | 0.00 |
| **Membership model (probability to belong to the choosy pooler class)** | **Estimate** | **S.E.** | **Est./S.E.** | **P-Value** | | | | |
| Age group (ref: age 18-24) | | | | | | | | |
| age 25-34 | 1.38 | 0.55 | 2.53 | 0.01 | | | | |
| age 35-44 | 1.62 | 0.55 | 2.94 | 0.00 | | | | |
| age 45-64 | 1.43 | 0.52 | 2.74 | 0.01 | | | | |
| age 65+ | 1.81 | 0.55 | 3.32 | 0.00 | | | | |
| Attitudes | | | | | | | | |
| Travel satisfaction | 0.15 | 0.07 | 2.09 | 0.04 | | | | |
| Environmentalism | -0.23 | 0.07 | -3.34 | 0.00 | | | | |
| Pro-multitasking on travel | -0.14 | 0.08 | -1.91 | 0.06 | | | | |
| Intercepts | -2.49 | 0.54 | -4.65 | 0.00 | | | | |
| Sample size | 1,190 | | | | | | | |
| Log-likelihood | -1722.428 | | | | | | | |
| AIC | 3520.855 | | | | | | | |
| BIC | 3713.960 | | | | | | | |
| Sample-size adjusted BIC | 3593.258 | | | | | | | |
| Entropy | 0.733 | | | | | | | |

*Notes*: 1. The choice model employs an ordered probit model with five levels of maximum acceptable additional travel time, such as no, 1-5 minutes, 6-10 minutes, 11-15 minutes, and 16 minutes or longer. 2. The unit of the wait time and travel costs are minutes and USD. 3. 999 indicates observations at a specific level are very few or non-existent in a given latent class. 4. Only three attitudinal factor scores in the membership model are continuous, and all the other variables are discrete. 5. Under the trip purpose, "Others" include two response categories, "To access public transit" and "Others (please specify)". Although the former category could differ substantially from the latter, it has only 16 trips (others initially had 63 trips), which makes it difficult to treat them separately in the estimation.

## 4.4. Profiles of rider characteristics and trip attributes

We also examine the profiles of trip attributes and rider characteristics for two purposes. First, although we find vastly different choice outcomes and preferences between the members of the two latent classes, a part of these differences could be attributable to their last RH trips happening to be quite different. Thus, we want to put the choice outcomes and preferences in the context of their actual RH trips. Second, many rider characteristics, although not statistically significant in the membership model, still help us further identify the characteristics of RH riders who would be more/less willing to respond to policies and programs aiming at increased pooling. After all, the two significant factors in the membership model, age and three attitudinal factors, do not inform us very much of target segments in the population, which are worth aiming for/better to avoid (because of high/low effectiveness).

As for the trip attributes of the last RH trip, some noticeable differences between the two latent classes are:

1. Choosy poolers made their last RH trips more during day time on weekdays (52.77%), compared to non-selective poolers (48.37%). In comparison, the former group requested for the trips less during night time on weekends (22.80%) than the latter (25.73%). Choosy poolers may have made their last RH trips under time constraints, while non-selective poolers may not have had such conditions. After all, time constraints could have easily prevented single-party riders from pooling with unknown passengers and spending longer while travelling.
2. In terms of travel costs, the last RH trip by the two classes do not differ much. That is, choosy poolers are *not* as much willing to travel with unknown passengers as non-selective poolers just because of their savings on time and money smaller than those of non-selective poolers. That is, other factors (either other trip attributes or rider characteristics) appear to play more critical roles here.
3. The size of one's travel party does not differ vastly between two classes; however, we still see some possibly meaningful differences. That is, choosy poolers have slightly larger portions than those of non-selective poolers for travelling together with other known passengers (↔ unknown passengers matched via ridehailing apps). The association of a larger travel party size (i.e., larger than one or solo travel) and less willingness to pool may indicate either (1) larger traveler groups can't comfortably share the in-vehicle space with unknown passengers, and/or (2) larger traveler groups value privacy (e.g., private conversation among them) more than smaller groups or solo travelers. Note that choosy poolers appear to consider the implication of pooling to their comfort or privacy during the RH journey, but non-selective poolers do not do so much.
4. As for trip purposes, choosy travelers hailed RH last time more for trips to airports than non-selective travelers. In fact, the latter travelled by RH more for shopping, social, and return-home trips. In part because of less-competitive public transit network and services in the study areas than old cities in the east coast (e.g., NY, Boston, and

Philadelphia), the proportions of the last RH trip for connecting to/from public transit facilities are quite small, 1.63% and 1.26% for the two classes respectively.

5. When asked about an alternative mode that individuals would have selected for the last RH trip had it not been for RH services, two classes present meaningful differences on a few options. Choosy poolers would have travelled more by motorized private modes including driving alone, driving with others (still as a driver, likely if the last RH trip was with other known passengers), and catching a taxi. By contrast, non-selective poolers would have selected shared means of transportation more, such as getting a ride (as a passenger) and catching a bus. Interestingly, choosy poolers would have travelled more by another form of public transit, light rail. Still, given its limited availability in the study areas, with its served areas being less affordable along with higher fares than those of conventional buses (i.e., more of its customer base are in higher socioeconomic status than those of buses), it is challenging to treat light rail as a similar shared mode as conventional buses.
6. Interestingly, smaller shares of choosy poolers would have cancelled their last RH trip if RH had not been available, than non-selective poolers. Choosy poolers may have had other feasible options for the trip, while non-selective poolers may have not. Alternatively, the former may have had to travel anyway, regardless of RH availability (e.g., having trips to airports more, which could have been impossible to cancel), while the latter could have easily cancelled the trip or have rearranged their activity-trip patterns on that day (e.g., having shopping and social trips more, which could have been discretionary).

As for the rider characteristics, some noticeable differences between the two latent classes are:

1. As for sex, a smaller proportion of female riders are found among the choosy poolers than among the unselective poolers. This appears to imply choosy poolers consist of male riders, likely employed more than female counterparts, whose trips may be more under time constraints. Such constraints may have prevented the choosy poolers from accepting a pooled ride, even with a very appealing discount.
2. Those in the racial majority group tend to belong to the choosy poolers than to the unselective poolers, and vice versa (80.17% and 74.34% respectively). Interestingly, less Asian or Pacific Islanders (in proportion) are found among the choosy poolers, who may be younger and tech-savvier than other racial/ethnic groups. In fact, a separate analysis reveals that this racial group is over-recruited in Austin, TX in part because of the major recruitment method for the city, Facebook advertisements. Obviously, users of social network services (SNS) tend to be younger, tech-savvier, and seeking travel multitasking/adventure more, which appear to be at work here.
3. On average, members of the choosy pooler class are more educated (e.g., those with a graduate degree 33.06% and 27.19% respectively), in part because many of the other class are still pursuing their final degree. For instance, while only 12% of choosy poolers are currently studying either full time or part time, 24% of unselective poolers, or twice

as many as their counterparts in choosy poolers, are still learning at schools, not yet finished in their education.

4. Choosy poolers have more convenient access to household vehicles, only 2.44% of them owning no household vehicles, in comparison to 5.08% of non-selective poolers not having their own car. Instead, two-vehicle households are represented more among choosy poolers than among non-selective poolers. their more car-centered travel behavior (and lifestyle in general) appear to account for larger proportions of them choosing private motorized modes (e.g., driving alone, driving with others, and hailing a taxi) as the alternative to RH services.
5. As for attitudes, factor scores on tech-savvy does not differ substantially in part because all cases in the study sample are RH users, who are tech-savvier on average than RH non-users. Also, it may suggest that accepting a pooled ride is not necessarily associated with one's knowledge of/technical skill for the shared service. Instead, the ways in which individuals link the shared service to environment impacts and productive/meaningful use of travel time matter more.
6. Interestingly, factor scores on pro-transit and pro-control do not differ much between choosy and non-selective poolers. As for the former attitude, both classes are somewhat negative on public transit to meet their travel needs, more than the average of the entire sample (N=3,465), indicating that pooled rides are not necessarily accepted as a smaller version of "public" transit, on which individual passengers meet and share space with quite many other passengers. In addition, one's preferences for control does not hold statistical power large enough to account for their decision to pool with unknown passengers. It may be the case that requesting for a ride that an unknown driver provides is already a compromise to one's proclivity towards control over the situation, and thus, accepting an additional stranger in the vehicle (as a fellow passenger) may not be viewed as serious threat by those with stronger preferences for control.

# 5. Discussions

## 5.1. Connections to the literature

As expected, most respondents (76.4%) belong to the class, whose members would accept pooled RH services for trips with longer *wait time* and more *costs*. After all, these two attributes are negatively associated with the utility of a given trip. Thus, when given an option to increase utility (i.e., reduce disutility) via a deep fare discount, respondents may well choose pooled RH services. What has not been discussed/found in existing studies is the (potential) presence of a group of RH users (23.6%), who would accept pooled RH services for trips with shorter wait time or cheaper fares. While this research cannot attribute preferences clearly to exact sources, we hypothesize that these RH users may feel more comfortable sharing shorter rides, instead of longer rides (and more saving on fares). For instance, these RH users may be concerned more on privacy while traveling with unknown passengers.

Respondents' preferences for/against pooling in relation to *trip purposes* are in stark contrast between two latent classes. Choosy poolers are the most willing to pool with strangers for work/school-related trips, but non-selective poolers would do so the least. Likewise, the latter would not mind pooling with strangers on their way home; however, the former would do so the least than trips with all the other trip purposes. In other words, the population (to be specific, the population of RH users) consists of distinct groups whose preferences for/against pooling could/do vastly differ in relation to key trip attributes, and their presence demands policy and planning tailored for each of these groups.

Interestingly, but perhaps not surprisingly, many of *socioeconomic and demographic characteristics* do not account for individuals' class membership. Only age remains statistically significant in predicting individuals' probabilities of belonging to choose poolers or non-selective poolers. While the RH literature presents a few factors (e.g., age, sex, race/ethnicity, education, income, and residential neighborhoods) accounting for the adoption of RH services, most of those factors do not explain the adoption of pooled RH services in this research. That is, factors affecting the adoption (or even frequency) of single-party RH services differ substantially from those underlying the adoption of pooed RH services. After all, the latter appears to be affected more by perceptions and preferences than by socioeconomics and demographics. In the meantime, age appears to capture the impacts of economic resources indirectly, which riders can/usually spend, or feel comfortable in paying for the RH services. Alternatively, age could reflect lifestyles at different stages in one's life, and more specifically, the characteristics of trips associated with those lifestyles (e.g., parents with a young child at home may not make as many late-night leisure trips as singles in twenty something).

In this research, we examine the role of *perceptions and preferences* in the adoption of pooled RH services, both those that were tested extensively in the recent literature and those that have not been studied very much. First, tech-savviness is ***not*** found statistically different between those who would be non-selective in pooling with unknown passengers and those would be choosy in doing so. Note that individuals in the study sample were already RH users, technologically savvier than non-users. Thus, choosy poolers are selective when choosing to pool, not because of their lower skill levels, but because of their stronger preferences for privacy or more concerns over privacy. After all, even the deep discount on fares could not persuade many of the choosy class to get pooled (see Figure 1).

Second, preferences for travel multitasking (similar to "interest in productive use of time" in Lavieri & Bhat (2019a)) are positively associated with individuals' probabilities of belonging to non-selective poolers. Note that in this research we cannot determine the direction of causality, and we believe travel multitasking and willingness to pool are likely to affect each other mutually. To be specific, travel multitaskers would not mind pooling with longer travel time very much because they can spend (part of) increased travel times for productive/meaningful activities, instead of wasting entirely. Equally likely (or even more likely), poolers (e.g., those who value savings on costs more than savings on time) may view travel multitasking to help them tolerate longer travel time, so they get to engage in it more, which leads to the development of positive attitudes towards it.

Third, environmentalism accounts for willingness to travel with unknown passengers, likely because of the potential of pooled services for lower pollution and greenhouse gas emissions per traveler. Note that in the literature, results are mixed in part because of sampling errors, inconsistent measurements, and more importantly, key outcomes being diverse (e.g., adoption of RH in general vs. choice of pooled RH for specific trips). In addition, given that the sample was collected from the U.S. South, this attitude may make a more distinctive difference between choosy and non-selective poolers, than it would do so in large historical cities in the North-eastern U.S., in which residents report stronger support for environmental policies than those in South on average.

Fourth, travel satisfaction, not yet examined in the literature in relation to the adoption of pooled RH to our best knowledge, is positively associated with the probability of belonging to choosy poolers. That is, those with satisfied more with their current travel routines are less likely to deviate from their routines and try new things. They may not want to get interrupted by uncertain travel times, unfamiliar routes, unknown passengers, or a potential chance of encountering unpleasant situations in relation to unknown passengers. In the meantime, unsatisfied travelers may not be particularly enthusiastic about pooling either, because the reasons for their dissatisfaction could be diverse: e.g., not satisfying the levels of travel time, travel costs, convenience, reliability, comfort, safety, privacy, etc. Still, discounted fares for those who value cost saving more than time saving may help them less dissatisfied with their current travel routines.

## 5.2. Implications and research methods

### *5.2.1. Contribution related to survey design and data collection*

To promote pooled RH services, we need to understand who would be willing to accept a pooled ride under what circumstances. While pursuing such an understanding, researchers employ stated-preference (SP) questions with a few scenarios considered more realistic than others. Although informative, these questions have critical limitations. First, SP questions may put respondents in travel contexts that they rarely encounter, contributing to less-reliable or less-relevant modeling results. Second, cognitive burdens associated with SP questions do not allow researchers to control for more than a few attributes. That is, researchers need to consider relative merits and drawbacks of asking questions in more detailed ways against asking those that are less mentally tolling. In this context, linking SP questions to reference trips that respondents made recently allows to effectively handle these challenges. It allows to collect information on/control for travel contexts that individuals did face, and it does not put response burdens any more than a typical Likert-scale question would do. By taking a hybrid approach, we could collect and analyze data that are realistic and still with rich details, without compromising data quality.

### *5.2.2. Contribution related to analytical methods*

Unlike previous studies (Lavieri & Bhat, 2019a, 2019b) investigating willingness to pool rides at the individual level, we model the adoption of pooled RH services at the trip level. The former approach allows to identify population segments that are on average more/less open to the idea of sharing in-vehicle space synchronously with unknown passengers. By contrast, the latter approach acknowledges that the same individual may present varying levels of willingness for pooled RH services, depending on travel contexts.

More importantly, we model taste heterogeneity in a way that enables to identify two groups of RH users, choosy poolers and non-selective poolers. The latter are more willing to accept pooled RH services, and the former use more discretion when deciding which RH trips to pool with unknown passengers. Consequently, their choice outcomes differ substantially between them: the majority of the latter (86.1%) would travel longer for the discounted fare, but most of the former (89.3%) reject to travel any longer with an unknown passenger for the same discount. These distinctive preferences and choice outcomes prove that, without considering taste heterogeneity among RH users, planners and policymakers cannot effectively promote pooling, while allowing increased energy consumption, air pollution, and GHG emissions to be unchecked at the expense of enhanced mobility in cities.

## 5.3. Implications to planning, policy, and practice

This research helps planners and policymakers promote the adoption of pooled RH services. To be specific, the analytical approach in this research presents a potential for the estimation of effects of policies, which aim at an increasing share of RH trips. Note that the choice model of LCCM allows to identify population segments who are more/less responsive to travel with unknown passengers in exchange of fare discounts. In addition, the membership model of LCCM enables to determine the extent to which a given level of fare discounts would convince the current riders on single-party RH to switch to pooled RH. Thus, with statistics on rider characteristics (e.g., age and attitudes) and trip attributes (e.g., wait time, travel costs, trip purposes, and travel party size) for a given region, transportation analysts are able to estimate the range of increases in pooled RH trips at the population level, for the 50% fare discount. As for these statistics, a few municipal governments including New York, NY, Chicago, IL, and Austin, TX mandate TNCs to provide detailed trip/passenger data on a regular basis to understand passengers' demand and better regulate the services for greater public benefits.

Many of these local governments also provide an anonymized version of these data publicly for research communities and the general public. In addition, with further information (e.g., the composition of TNC fleets), planners and policymakers are able to estimate savings in energy consumption, air pollution, and GHG emissions per capita basis.

Polished survey designs and data collection will greatly expand the scope of estimation for policy effects. For instance, increasing the number of SP questions with varying levels of key trip attributes would allow to estimate effects under multiple scenarios. The survey whose data we analyze in this research asked only one question for each respondent with a fixed level of fare discount, 50%, to reduce their response burden. In a follow-up survey, researchers may want to ask each individual multiple questions with varying levels of fare discounts or with one trip attribute manipulated at each time (e.g., number of additional unknown passengers). Also, to increase the applicability of estimation results into data without qualitative information (e.g., perceptions and preferences), analysts can estimate integrated choice and latent variable (ICLV) models, in which individuals' socioeconomic demographic characteristics are modelled to account for their latent attitudes. With ICLV results, researchers are able to apply key parameter estimates to conventional trip-diary survey data, widely adopted by most transportation agencies in standardized formats and less expensive prices. These estimates help planners and policy makers determine the lower and upper bounds of policy effects, with which they will be able to demand TNCs to achieve as a condition for continued operation. After all, TNCs are motivated not to target greater shares of pooled trips (good for society) but to maximize revenues and profits (good for private businesses).

As for effective policies aiming at increased pooled trips, recommendations include the followings. First, for choosy poolers, who would travel with unknown passengers the most for work/school-related trips, running large-capacity vehicles along major transportation corridors during the morning/evening peak hours would be effective. Second, features that improve safety and privacy of RH passengers would help address concerns. Such features include direct-call buttons inside RH vehicles or links on smartphone apps for immediate help, proper screening for ridehailing drivers, collaborations with local police departments, and making recordings of in-vehicle situations (which would be kept for a limited period). Third, better in-vehicle environments for travel multitasking will be effective in attracting those who prefer productive/meaningful use of travel times to pool instead of travel alone: e.g., well-lit interior designs with less vibration and reduced distraction among passengers. Fourth, education campaigns that aim to increase the awareness of environmental impacts of low-occupancy vehicle trips would lead RH users to adopt the preferences of non-selective poolers, instead of those of choosy poolers.

# 6. Conclusion

## 6.1. Summary

In this research, we examine individuals' preferences for/against pooled RH services for their last RH trip, by considering both trip attributes and rider characteristics. In doing so, we model taste heterogeneity in a way that assumes unobserved groups (i.e., latent classes), each with unique preferences, are present in a given sample of RH riders (N=1,190 in four metropolitan regions in the U.S. South for June 2019 to March 2020). Our chosen statistical mode, LCCM, allows us to identify the unique forms of heterogeneous preferences while simultaneously examining the association of covariates with the probabilities of belonging to each class. We find two latent classes with qualitatively different preferences, choosy poolers and non-selective poolers, regarding their choice for/against pooling based on the wait time, travel costs, purpose, and travel party size of the last RH trip. We also identify personal characteristics, age and three attitudes (travel satisfaction, environmentalism, and travel multitasking), which account for individuals' class membership. Along with a rich set of covariates, we describe the unique profiles of trips and individuals in each class separately.

## 6.2. Contributions

This research makes important contributes to the literature and practice in the following ways. Theoretically, this research expands the current knowledge about RH users' preferences for/against pooling. For instance, members of two latent classes present preferences in the opposite directions regarding which trip purpose(s) they would accept pooled services for. Their heterogeneous preferences suggest the presence of two groups in the population: one with higher sensitivity towards privacy/safety issues while traveling with strangers, and the other with less concerns about them. Note that these preferences are associated with age and attitudes towards the environment, travel multitasking, and travel satisfaction. In addition, we analyze data collected in four metropolitan areas in the U.S. South, well-known for their car-oriented travel behaviors and development patterns. Although the data do not allow us to fully examine the role of region-wide modal style (i.e., modality) and mobility culture, the conceptual framework and analytical results in this research will be useful for researchers when developing comparative studies with more transit-oriented metropolitan areas.

Methodologically, this research makes at least two contributions. First, we analyze data at the trip level (i.e., examine the effects of trip attributes on the choice of pooling), which enables a nuanced realistic understanding on willingness to pool with unknown passengers. Note that, existing studies at the individual level often estimate "average" effects of personal/household/land-use/attitudinal traits on the choice of pooling. However, the same individuals may accept pooled rides depending on unique travel contexts, which these studies did not consider. Second, we take a hybrid approach when measuring the extent to which individuals would accept pooled rides. To be specific, instead of "pure" SP questions, the survey asked a hypothetical question in reference to the late RH trip that individuals made actually. Such a combination of RP and SP enables to collect various trip attributes, improve the realism of the hypothetical question, and increase reliability of respondents' answer while reducing response burdens.

Practically, this research suggests effective analytical approaches, latent-class ICLV, for the estimation of region-wide effects of specific policy options aiming at the promotion of pooled RH services. We estimate a basic LCCA (e.g., one that consists of a membership model and a choice model, but not a measurement model linking attitudinal statements and socioeconomic traits) in this research, which requires attitudinal statements in input data. By contrast, incorporating a measurement model into the basic LCCA allows modeling results to be applicable to data without attitudinal statements (Vij & Walker, 2016). After all, most regional travel surveys in the U.S. take a typical trip-diary format, which lacks attitudinal statements. In this context, latent-class ICLV would allow transportation analysts to predict changes under hypothetical scenarios (e.g., varying levels of fare discounts for pooled rides, raised environmentalism via education campaigns, enhanced travel multitasking via in-vehicle design updates, and improved/worsened travel satisfaction) via changes in both the latent-class composition and choice outcomes in a region.

## 6.3. Limitations & future directions

This research has several limitations, and below we discuss them in detail and suggest directions for future research. A lack of some trip attributes does not allow us to separately estimate their effects on respondents' choice of maximum acceptable additional travel time. These attributes include the built environment characteristics at the origin and destination of trips, departure/arrival time, and trip attributes (e.g., travel time and costs) of available alternatives. Also, choosy poolers' negative coefficient estimates on wait time and travel costs appear to capture unobserved characteristics of their last RH trips, and richer information on these last trips would allow us to identify what these characteristics would be: e.g., information on safety and privacy. In a similar vein, it would be ideal to include attitudes found highly relevant during the COVID-19 pandemic: e.g., perceptions and preferences related to hygiene, cleanness, effectiveness of safety/prevention measures taken by TNCs, and potential transmission risks of the driver (or matched unknown passengers).

A simple SP question in this research is proven sufficient to reveal the presence and nature of heterogeneous preferences in a sample of RH riders; however, a series of SP questions would enable more sophisticated analyses, which would generate additional useful insights into choices related to pooling and effective policies that promote it. For instance, one scenario was presented to each respondent with too generous a level of fare discounts. Multiple scenarios would allow to examine the effects of varying levels of fare discounts (e.g., 10%, 30%, and 50%) and those by other attributes (e.g., number of additional matched passengers). In addition, it would be informative to examine the asymmetric effects of fare differences on acceptance of pooling. To be specific, instead of fare discounts, scenarios can include "surge pricing" for single-party RH trips, which could be avoided by pooling with unknown passengers. With the same amount of fare differences between single-party and pooled rides, whether respondents would respond to fare increases (e.g., surge pricing, which could be avoided by pooling) and decreases (e.g., fare discounts, which could be earned by pooling) the same ways will shed further light on consumer behaviors and support effective policy formulation.

Alternative data collection efforts will help overcome some of limitations inherent to the survey data in this research. First, the last trip may not represent a typical use case for each respondent, and collecting information on multiple RH trips would allow to examine inter-personal and intra-personal taste heterogeneity. Second, it will be fruitful to collaborate with TNCs such as Uber and Lyft in the U.S. market on recruiting survey respondents and collecting high-resolution attributes of their RH trips. The RH literature includes studies employing either small-sized survey data with rich qualitative information or high-resolution massive trip data that lack individuals' characteristics, but not both. In this context, collaboration with TNCs enables to overcome limitations of each data collection approach while combining unique merits from each. Last but most importantly, a longitudinal analysis on survey data collected via the same sampling frame will be highly informative, especially as the ongoing pandemic has brought us unprecedented massive-scale disruptions to everyday life and has led individuals to rebuild travel routines and society to reflect on effective infrastructure management.

In this research we employ an ordered logit model to examine relationships of trip attributes and pooled rides; however, advanced choice models would help more accurately understand the ways that various factors affect individuals' choice of pooling. Such models include generalized ordered logit, nested logit, and joint modeling of RP and SP. The first relaxes the proportional odds assumption of the ordered logit, which reveals more realistic travel behaviors. The second takes a two-step approach, in which individuals are assumed to choose whether to pool or not, and if they accept pooling, they determine how much they would accept additional travel time. After all, zero-minute maximum additional travel time may not always indicate no intention for pooled rides. Instead, it may present very high opportunity costs for travel time even if travelers have some (not too much) intention for pooling. The third incorporates individuals' actual choice into the model of their hypothetical choice, which allows to examine more nuanced, complex relationships that univariate models cannot examine.

Results in this research are prone to sampling bias, especially cases collected in Austin, TX, which were recruited via social media advertisements. After all, their sampling frame is not clearly known to researchers and to the general public yet. In addition, comparative studies with old cities such as NY, Boston, and Chicago would help understand the role of extensive transit infrastructure in one's willingness to share rides with unknown passengers. After all, the U.S. South do not have transit services as well developed as those in East/Northwest counterparts. Residents in the latter may behave differently from those in the former in part because they are more familiar with transit and sharing in-vehicle space with strangers.

## Table 5. Attitudinal statements and factor loadings (N=3,338)

| Statements | Pro TOD | Pro multitasking | Travel satisfaction | Tech-savvy | Unitasking | Pro transit | Environmentalism | Pro control |
|---|---|---|---|---|---|---|---|---|
| I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area. | 0.777 | | | | | 0.194 | | |
| I prefer to live in a spacious home, even if it is farther from public transportation or many places I go. | -0.659 | 0.152 | | | | | | |
| I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood. | 0.379 | 0.199 | | | | | | |
| I like trying things that are new and different. | | 0.618 | | | -0.179 | | | |
| I try to make good use of the time I spend traveling. | | 0.550 | | | | | | |
| The reliability and quality of a car are more important than its brand. | | 0.295 | | -0.229 | | | | |
| Having internet connectivity everywhere I go is important to me. | | 0.260 | | 0.238 | | | | |
| The level of congestion during my daily travel bothers me. | | | -0.570 | | | | | |
| My daily travel routine is generally satisfactory. | | | 0.519 | | | | | |
| The time spent traveling to places provides a useful transition between activities. | | 0.197 | 0.327 | | | 0.184 | | 0.167 |
| Having to wait can be a useful pause in a busy day. | | 0.158 | 0.282 | | | | 0.238 | |
| Learning how to use new technologies is often frustrating for me. | | -0.163 | | -0.494 | | | | |
| I like to be among the first people to have the latest technology. | | 0.156 | | 0.483 | | | | 0.253 |
| Sharing my personal information or location via internet-enabled devices concerns me a lot. | | | | -0.358 | | | | |
| I prefer to shop in a store rather than online. | | | | -0.276 | | | | |
| I would be fine with renting out my car to people I do not know. | | | | 0.220 | | | 0.180 | |
| I feel uncomfortable around people I do not know. | | | | | 0.552 | | | |
| I prefer to do one thing at a time. | | | | | 0.433 | | | |
| I am too busy to do many of the things I like to do. | | | -0.182 | | 0.407 | | | |
| I tend to feel sick if I read while in a moving vehicle. | | | | | 0.182 | | | |
| Public transit is a reliable means of transportation for my daily travel needs. | | | | | | 0.634 | | |
| Most of the time, I have no reasonable alternatives to driving. | | | | | 0.184 | -0.486 | | |
| I am committed to an environmentally-friendly lifestyle. | | | | | | | 0.665 | |
| I am committed to using a less-polluting means of transportation (e.g., walking, biking, and public transit) as much as possible. | | | | | | 0.216 | 0.597 | |
| The government should raise the gas tax to help reduce the negative impacts of transportation on the environment. | 0.240 | | | | | | 0.374 | |
| When traveling in a vehicle, I prefer to be a driver rather than a passenger. | | | | | | | | 0.546 |
| I definitely like the idea of owning my own car. | | 0.242 | | -0.181 | | -0.179 | -0.192 | 0.406 |
| Car crash deaths are an unfortunate but unavoidable part of a modern, efficient transportation system. | | | | | | | | 0.155 |

*Notes*: The pattern matrix is taken from SPSS outputs; Factor loadings smaller than 0.15 are suppressed for brevity; Extraction method: Principal Axis Factoring; Rotation Method: Oblimin with Kaiser Normalization; and Factor score computation method: Bartlett.

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## Data Summary

### Products of Research

The data used for the analyses were collected with a survey designed and administered through a grant from the Tier 1 TOMNET (Teaching Old Model NEw Tricks), which is funded by the U.S. Department of Transportation through the University Transportation Center program.

This dataset consists of survey data collected with a transportation survey in four metropolitan areas in the U.S. South between June 2019 and March 2020 with a focus on new mobility services and technology (N=3,365 for the total sample, with the information from a subsample of 1,190 ridehailing users that was used for the analyses in this report). The data includes information on the personal attitudes and preferences, lifestyles, adoption of social media and ICT, e-shopping patterns, residential location, living arrangements, recent major life events, commuting and other travel-related patterns, auto ownership, awareness, adoption and frequency of use of shared mobility (bikesharing, e-scooter sharing, ridehailing services, pooled ridehailing services), propensity to purchase vehicle and/or modify vehicle ownership, perceptions and propensity to adopt driverless vehicles, propensity towards shared or personal ownership and use models of driverless vehicles, and sociodemographic traits.

### Data Format and Content

The data file is available in a .sav file from the SPSS system.

Database: Each row represents a single survey respondent with a unique ID number assigned, and each column corresponds to one variable.

### Data Access and Sharing

The final data of this project is subject to the Georgia Institute of Technology Institutional Review Board (IRB) guidelines on the treatment of human subject data and could be made available, in a heavily edited version with no personal identifiable information (PII), upon request from the principal investigator.

### Reuse and Redistribution

The final data of this project is subject to the Georgia Institute of Technology Institutional Review Board (IRB) guidelines on the treatment of human subject data and could be made available, in a heavily edited version with no personal identifiable information (PII), upon request from the principal investigator. For all purposes allowed by the IRB guidelines, there are no further restrictions to the use of the data. Data can be reused and redistributed with credit to this report and the authors of the research and to the funding agency that funded the original data collection.