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Discussion Paper

Consumer Preferences for Ride-Hailing

The Barriers to an Autonomous, Shared, and Electric Future

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About KAPSARC

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Key Points

Research has shown that when combined in a mobility-on-demand (MOD) framework, automation, carpooling, and electrification have the potential for theoretically large emission reductions. However, there is insufficient research regarding the consumer preferences for and behavioral responses to this vision of transportation in the future. In this paper, we use choice experiment data collected from an online ride-hailing survey to quantify the consumer preferences for these technologies.

- Our results suggest that there are major barriers to consumers' willingness to ride in such vehicles.
- We find that respondents require large discounts to ride in driverless vehicles or to carpool with other passengers, even when ride times are held constant. Although they are open to riding in electric vehicles (EVs) and hybrid electric vehicles (HEVs), they are not willing to pay more to do so.
- Safety concerns and an unwillingness to ride with strangers appear to be the primary drivers of these preferences.

1. Introduction

A major focus of current transportation research is mobility on demand (MOD) or mobility as a service. The visualization of such services often conjures a picture of a self-driving car that appears futuristic and that can be ordered via a cell phone. In the framework of Sperling (2018), the vision centers on three pillars or "revolutions:" electrification, pooling, and automation. Ride-hailing can be considered a foundation for this framework.

The use of ride-hailing services has increased substantially in the last decade. Uber, which started in 2009, was available in 404 cities worldwide in 2016 (Li et al., 2016) but is now present in 10,000 cities.[1] Ola, which was founded in India in 2010, is now available in more than 200 cities.[2] Didi Chuxing, which launched in China in 2012, now serves more than 550 million riders in 16 countries.[3] The ridership of vehicles from these and other platforms will likely continue to grow in both the developed and developing worlds. From 2015 to 2018, the share of American adults who had used a ride-hailing service increased from 15% to 36%.[4] Autonomous vehicles (AVs) could revolutionize ride-hailing and MOD, especially given their projected lower cost per mile (e.g., Bösch et al., 2018). In fact, AVs are projected to increase mobility access for elderly people and those with disabilities (Fagnant and Kockelman 2015; Harper et al. 2016). However, the lower cost will likely increase usage, vehicle miles traveled (VMT), and congestion (Oh et al., 2020; Wadud, MacKenzie, and Leiby 2016). Therefore, fleet electrification and carpooling (i.e., multiple passengers with similar origins and destinations sharing a vehicle) will be crucial for realizing environmental benefits such as emission reductions (Chen, Kockelman, and Hanna, 2016; Fagnant and Kockelman, 2018; Jenn, 2020).

There is a relatively large scope of engineering and operations research on AV usage, as well as algorithm optimization and carpooling for emission reductions (e.g., Hasan, Van Hentenryck, and Legrain 2020; Liu et al. 2019). However, while the theoretical impacts and emission reductions have been quantified, relatively little is known about the behavioral component, which will determine how consumers use these technologies in practice. In this paper, we use the results of a choice experiment embedded in an online survey to investigate the consumer preferences for ride-hailing, particularly in the context of AVs, electric vehicles (EVs), and carpooling. Specifically, we utilize the results of the choice experiment to estimate discrete choice models, run simulations to assess consumers' price sensitivity to ride-hailing, and quantify the consumer preferences for riding in AVs, EVs, and carpool vehicles. We explore the heterogeneity in preferences and assess the overall implications for the future ridership of an electric and autonomous on-demand fleet.

2. Literature Review

AVs are expected to lower the per-mile costs of ride-hailing. Bösch et al. (2018) find that labor accounts for nearly 90% of the per kilometer costs of a taxi ride in Switzerland and that automating taxis would reduce the per kilometer costs by nearly 85%. Chen, Kockelman, and Hanna (2016) estimate that in the USA, the total per-mile cost of a shared vehicle, an EV, and AV ($0.42-$0.49) would be on par with the per-mile costs of private vehicle ownership for lower-mileage households. Lower costs per mile and increased access combined with "dead-heading" (miles without passengers) are projected to increase VMT. Oh et al. (2020) estimate that in Singapore, a moderate adoption of automated MOD would increase VMT by 13%. Fagnant and Kockelman (2018) estimate that the VMT in Austin, Texas, would increase by 8% without dynamic ride-sharing or carpooling passengers. Similarly, Wadud, MacKenzie, and Leiby (2016) estimate a 2%-10% increase in VMT across the USA, and Harper et al. (2016) estimate a 14% annual increase in VMT in the USA. Thus, despite AVs' potential for emission reductions from eco-driving, vehicle right-sizing, and de-emphasized performance (Liu et al. 2019; Wadud, MacKenzie, and Leiby 2016), without electrification and pooling, the automation of ride-hailing could actually lead to an increase in carbon dioxide emissions. Wadud, MacKenzie, and Leiby (2016) find that, depending on competing effects (e.g., changes in travel demand, the type of fuel, vehicle operation), emissions and energy use could either halve or double.

Meanwhile, the optimization of passenger matching algorithms has shown that carpooling can lead to substantial emission reductions. For example, Hasan, Van Hentenryck, and Legrain (2020) show that carpooling can lead to a 57% decrease in vehicle usage and a 46% decrease in VMT, with only a 22% increase in ride times. Electrification can also substantially reduce transport emissions, particularly in the ride-hailing context, especially when combined with a low-carbon grid. Jenn (2020) shows that in California, switching a ride-hailing vehicle from an internal combustion engine (ICE) vehicle to an EV results in three times greater reductions in emissions than switching a private ICE vehicle to an EV due to the greater usage intensity of ride-hailing vehicles.

Various studies have explored the general consumer interest in AVs. To explore the preferences for and attitudes toward AVs, Nazari, Noruzoliaee, and Mohammadian (2018) use stated preference data from a survey in the state of Washington to estimate ordered probit models. They find that people with "green travel patterns," as well as those with a positive preference for MOD technologies, are more likely to be interested in AVs. However, safety concerns hinder people's interest in AVs. They also find that respondents with longer commutes are more likely to be interested in AVs. However, those with larger daily VMT do not favor AVs for other day-to-day trips, presumably because people could utilize their commute to work productively. Asgari and Jin (2019) survey drivers in major metropolitan areas in the USA, asking how much more they are willing to pay for various automation features in their private vehicle. They find that technology-savvy respondents were more likely to be interested in AV adoption, while those with a "joy of driving" were the least interested. Pettigrew, Dana, and Norman (2019) use survey data from Australia to estimate the latent profiles of AV adopters. They categorize respondents into five classes, finding that 29% would not adopt AVs and that 14% would be "first movers" and be highly interested in AV adoption. The authors use sociodemographic and attitudinal variables to segment respondents. Wali, Santi, and Ratti (2021) analyze data from the 2017 California Vehicle Survey and find that respondents who participate in carshare and rideshare programs, as well as those who more frequently utilize public transportation, have a greater affinity for AVs. They also find that EV ownership is positively correlated with AV affinity.

Independent of electrification and automation, the adoption of ride-hailing could impact greenhouse gas (GHG) emissions; for example, it could impact vehicle ownership and VMT. Ward et al. (2019) use a difference-in-differences approach and find that the entry of Uber and Lyft into markets in the USA from 2005 to 2015 led to a 3% decrease in per capita vehicle registrations and likely led to a decrease in emissions. Subsequently, Ward, Michalek, and Samaras (2021) find that these ride-hailing services led to a 50%-60% reduction in local air pollutants due to the avoidance of "cold starts" and because the vehicles were newer and cleaner. However, they also find that the extra miles driven without passengers (i.e., "dead-heading") led to a 20% increase in fuel consumption and GHG emissions. They note that this issue could be mitigated through electrification and carpooling.

Another important factor for the emission-related benefits of ride-hailing is how it affects public transportation. Regarding this topic, the literature is somewhat mixed. For example, while some studies have shown that ride-hailing has replaced the market share of public transportation to a certain extent (e.g., Graehler 2019), others have shown that ride-hailing has increased public transit use in certain contexts (e.g., Berrebi 2020; Hall et al. 2019) because it helps solve the "last mile" problem (Huang 2021). However, others find no significant impact (e.g., Boisjoly et al. 2018).

Several studies have focused on ride-hailing preferences. In a survey of Americans, Naumov and Keith (2019) ask respondents to choose between a private ride, such as UberX or Lyft, and a pooled ride, such as UberPOOL or LyftLine. They find that consumers prefer less expensive trips and that lower-income riders are more likely to choose the pooled ride. Asgari, Jin, and Corkery (2018) employ a choice experiment of major metropolitan areas in the USA where respondents choose between driving a private vehicle, using an exclusive on-demand service, or using a shared on-demand service with varying travel times, travel costs, and the potential for multitasking. They find that monthly travel cost savings of $72 or time savings of 16 minutes per trip would persuade half the sample to switch from private vehicles to ride-sharing. Furthermore, they find that while most respondents prefer exclusive services over those shared on demand, regular transit users are more open to shared rides.

In this paper, we focus on the intersection of ride-hailing, automation, electrification, and carpooling. To complement the literature on the potential impacts and benefits of these technologies, we investigate the behavioral aspects of this future vision of transport. Specifically, we quantify the consumer preferences for these different technologies. While there is research on the consumer preferences for each of these individual technologies, few studies examine the intersection of ride-hailing and AVs, and no studies explore the intersection of all four components (i.e., ride-hailing, automation, electrification, and carpooling).

A small number of recent papers explore the intersection between the consumer preferences for ride-hailing, carpooling, and AVs (but not EVs). In a choice experiment conducted by Lavieri and Bhat (2019), respondents are asked to choose between a private self-driving cab service and a shared service, with varying travel times, costs, and additional passengers. Respondents are also told to assume that all rides involve self-driving vehicles. They use choice models and find that respondents are less sensitive to carpooling with a stranger while commuting than to carpooling with a stranger during a leisure trip. Furthermore, they conclude that the additional travel time caused by carpooling is more of a barrier to carpooling than the presence of a stranger. Given that all rides are assumed to be self-driving, they do not quantify AV preferences.

Irannezhad and Mahadevan (2022) survey Australians and ask how likely they are to choose carpooled and self-driving ride-hailing services for different types of trips, assuming that carpooling may reduce costs by as much as 50%. The respondents then rank how important time delays, priority drop-off, and walking distance are to their various trip types and how much of a discount they would require to share their ride. The results show that frequent transit users are more likely to use ride-hailing services, people with "tech-centric" and "anti-driving" attitudes are more likely to choose pooled rides as well as AVs, and nearly half of the respondents would not choose an AV even with a 50% price discount.

Webb, Wilson, and Kularatne (2019) explore the consumer preferences in Queensland, Australia, for substituting 50%-80% of private vehicle trips with shared vehicle, EV, and AV trips. These authors vary the cost per kilometer, the annual number of accidents in the state, increases in urban space due to decreased parking space, and extra travel time due to congestion. Only 16% of survey respondents chose the status quo option of continuing 100% private vehicle use, and in this regard, the most motivating attribute was cost.

Sweet (2021) uses a choice experiment of Canadians in which respondents choose from five different transportation modes: driving in a private car, cycling, riding in an on-demand car, taking transit plus an on-demand car, and taking transit plus walking. The on-demand cars may or may not have a driver or additional passengers, the transit may or may not be a driverless shuttle, and the travel time and cost also vary across options. The estimated choice models suggest that carpooling with another passenger is associated with a $1-$4 penalty. However, the estimated coefficients for driverless rides are not statistically significant, which is perhaps due to limited power given the large number of estimated coefficients. While Sweet's (2021) paper is the closest to ours methodologically (utilizing both a choice experiment and estimating mixed logit models), it better characterizes preferences across modalities. In contrast, our paper better characterizes ride-hailing preferences and more richly quantifies tradeoffs between price, carpooling, and vehicle technology, including EVs and hybrid EVs (HEVs), which are not covered in Sweet (2021). Furthermore, we obtain more precise coefficients of driverless and autonomous attributes and more fully characterize the distribution of these preferences and their interactions with other preferences.

Unlike the literature, our paper examines the preferences for ride-hailing, automation, electrification, and carpooling, all of which are combined in a single context that better reflects the automated, carpooled, and electrified future vision of transport. Furthermore, we use an experimental approach combined with choice models rather than the descriptive surveys and summary statistics used by the majority of studies. Doing so allows us to quantify the willingness to pay (WTP) for various technologies and attributes and to perform simulations. We also focus exclusively on ride-hailing decisions (i.e., substitution across ride-hailing options) rather than the decision to ride-hail (i.e., substitution across transport modes). Finally, the literature focuses more on sociodemographic and psycho-behavioral factors that influence ridership (i.e., who will likely use these technologies), while our paper focuses more on fully characterizing the preferences and interactions between ride types. As one of the first papers to focus on the behavioral side of the automated, carpooled, and electrified MOD vision of the future, we offer several key takeaways regarding how future markets may develop, as well as anticipated barriers.

3. Data

In May 2022, we developed and deployed a national online survey of 750 adults in the USA who had used a ride-hailing service such as Uber or Lyft; the sample is representative in terms of age, income, and race/ethnicity.[5] On average, the respondents took just over seven minutes to complete the survey, with a median completion time of six minutes. An introductory script included a consequentiality statement to reduce hypothetical bias (Lloyd-Smith, Adamowicz, and Dupont 2019; Oehlmann and Meyerhoff, 2017).[6] After two screening questions were asked to ensure that each respondent was at least 18 years of age and had previously used a ride-hailing service,[7] the survey collected basic sociodemographic information, as well as the respondents' experiences with ride-hailing services. Next, the survey introduced and administered a choice experiment in which the respondents selected their preferred ride out of two ride-hailing options, with an outside option to select neither. Several follow-up questions sought to better understand the respondents' motivations for their choices. The survey concluded with a short series of attitudinal questions.

The choice experiment was divided into two parts: short trips and long trips. The respondent was first told the following: "Now, suppose that you have decided to use a ride-hailing service (Uber, Lyft, or other) on a relatively short trip. For example, this trip could be to a restaurant, bar, or friend's place." The trips varied in terms of price, ride time, carpooling, type of vehicle, and self-driving technology.[8] These attributes and their levels are shown in Table 1. The vehicle type options included HEVs, battery-powered electric vehicles (i.e., EVs), or neither (i.e., standard ICE vehicles). The self-driving technology was fully autonomous (driverless), partially autonomous (self-driving technology with a driver in the car), or neither. Notably, in our modeling, this attribute was split into two: autonomous (whether the vehicle uses self-driving technology) and driverless. After each of these attributes was introduced, the respondents were asked two comprehension questions and a consequentiality question.[9] Both of the comprehension questions were answered correctly by more than two-thirds of the respondents. Those who selected the wrong answer were shown why they were wrong and given the correct answer. Next, the respondents were shown three choice sets. In each choice set, they were asked to select their preferred ride, with an option to select neither.[10] An example choice set is shown in Figure 1.

Table 1. Choice experiment attributes and levels.

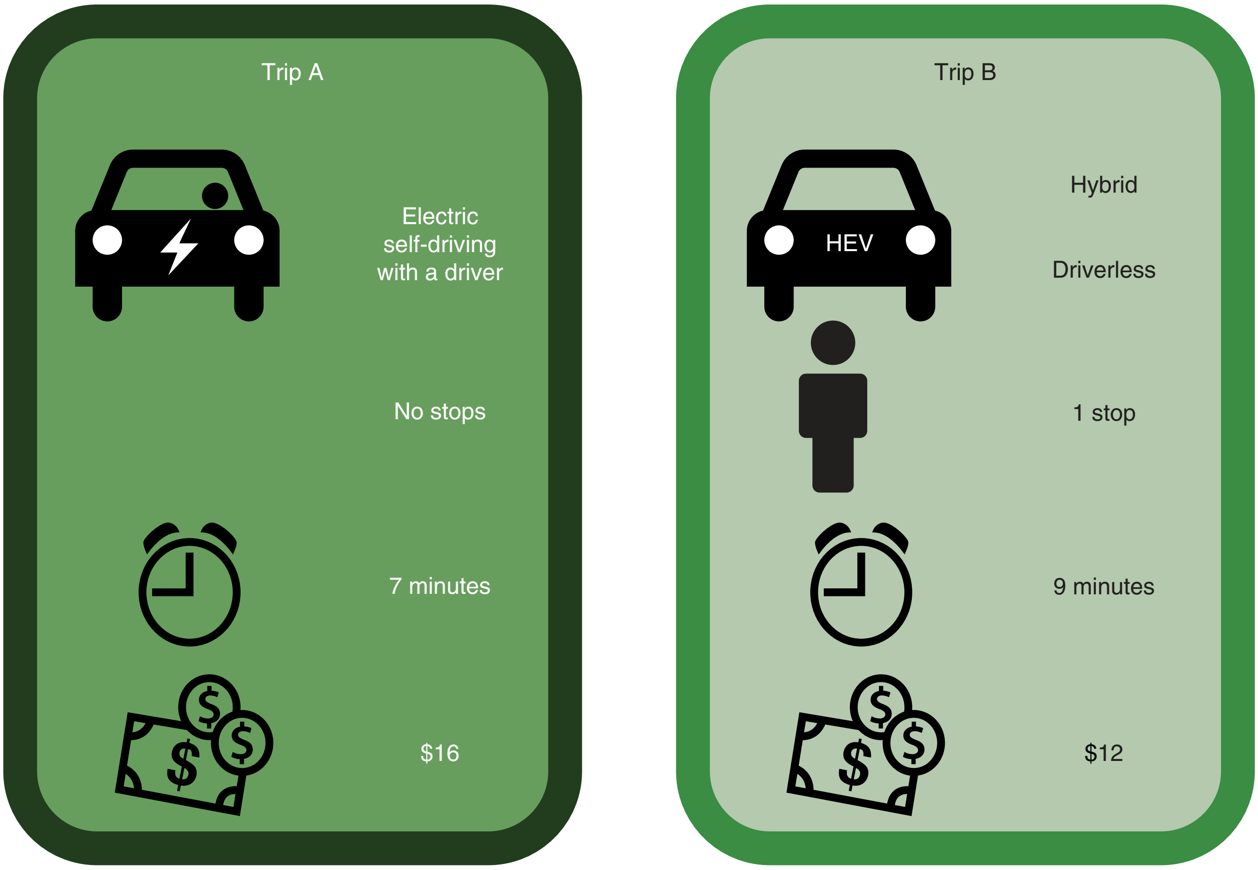
Attribute	Type
Vehicle	HEV, EV, neither
Self-driving technology	Fully autonomous/driverless (self-driving with no driver), partially autonomous (self-driving with a driver), neither
Carpooling (Number of stops to pick up an additional rider)	0, 1, 2
Short ride	
Ride time (minutes)	7, 9, 11, 13
Price (dollars)	12, 14, 16, 18, 20
Long ride	
Ride time (minutes)	35, 45, 55, 65
Price (dollars)	55, 65, 75, 85, 95

Notes:

*The ride time and price are based on the following information. Jones (2023) states that "the average Uber/Lyft trip distance is 5–6 miles and takes around 10 minutes to complete"; additionally, "long trips are mostly four times or five times the average ride distance and take much longer to complete. For example, we can consider a trip 'long' when the distance covered is over 10 miles or takes over 45 minutes to complete." Forbes (2015) states that "according to Sherpashare, a company that sources ride data and provides driver analytics, the average Uber ride is 5.41 miles." Lisa (2021) states that "the average Uber or Lyft fare used to be predictable and steady — about $25–$26 from mid-2018 through the runup to the virus, according to Statista." Finally, assuming a driving speed of 20 miles per hour (to account for stops) results in an average fare of $1.57 per minute ($25.5/5.41 mi*20 mi/60 minutes=$1.57 per minute). In the choice experiment, the average per-minute cost is $1.60 ($16/10=$1.6) for short trips and $1.50 for long trips ($75/50=1.5).*

Source: KAPSARC.

Figure 1. Example choice set



Source: KAPSARC.

The respondents were then asked to envision a scenario: They had decided to hail a ride for a somewhat longer trip, such as to an airport or a concert/sports venue. They were then shown three more choice sets with longer ride times and higher price points, as shown in Table 1.

The choice experiment was designed using Ngene software. The experimental design was based on the following utility (v_i) function for choosing ride i:

$$v_i = \beta_1 partial_i + \beta_2 autonomous_i + \beta_3 HEV_i + \beta_4 EV_i + \beta_5 number\_stops_i + \beta_6 ridetime_i + \beta_7 price_i \quad (1)$$

We used an algorithm that sought to minimize the variance–covariance estimator of the vector of the coefficients from Equation 1. Doing so resulted in a design that maximized the information gained from the choice experiment. Specifically, the algorithm varied the alternatives within choice sets and the choice sets within an experimental design to minimize the D-error—the determinant of the asymptotic variance–covariance matrix. To further improve the efficiency of the experimental design, we specified Bayesian priors to indicate that β_5, β_6, and β_7 would likely be negative. Informing the experimental design of the anticipated coefficient sign can substantially improve design efficiency (Scarpa and Rose 2008). Our choice experiment included 20 choice sets each for both short and long trips. Three of each were randomly selected for presentation to the respondent.

4. Empirical Model

We model the probability of choosing a ride as a function of its attributes. The probability of a respondent choosing ride *i* (π_i) is the same as the probability that the utility from choosing ride *i* is greater than the utility of choosing any other ride:

$$\pi_i = Prob(u_i > u_j)\ \forall j \neq i, \tag{2}$$

where

$$u_i = v_i + \varepsilon_i \tag{3}$$

If we assume that the error terms ε_i are independently distributed Type I extreme value errors, we can model the probability of choosing ride *i* as a mixed logit:

$$\pi_i = \frac{\exp(v_i)}{\sum_{k=1}^{K} exp(v_k)} \tag{4}$$

Unlike a conditional logit, a mixed logit allows for heterogeneous preferences. The mixed logit relaxes the property of independence of irrelevant alternatives of the conditional logit and allows coefficients to be random parameters with normal distributions rather than fixed parameters (Train 1998). In the mixed logit the probability of choosing ride *i* is as follows:

$$\pi_i = \int \frac{\exp(\boldsymbol{x_i}'\boldsymbol{\beta})}{\sum_{k=1}^{K} exp(\boldsymbol{x_k}'\boldsymbol{\beta})} f(\boldsymbol{\beta}|\boldsymbol{\theta})\, \partial\boldsymbol{\beta}, \tag{5}$$

where $\boldsymbol{x_i}'\boldsymbol{\beta}$ is the vector of attributes of ride *i* from Equation 1 multiplied by a vector of coefficients and $f(\boldsymbol{\beta}|\boldsymbol{\theta})$ is the density of $\boldsymbol{\beta}$. When modeled as random parameters, we assume that the coefficients of the price, ride time, and number of stops are log-normally distributed—a common assumption for price and other parameters that are expected to be strictly positive or negative. This approach also avoids the issue of an undefined standard error for WTP estimates (Carson and Czajkowski 2019).

Once the coefficients from Equation 1 are estimated, we calculate the WTP for a 1-unit change in an attribute *x* as $\beta_x/{-\beta_7}$ when β_7 is specified to have a normal distribution, $\beta_x/\exp(\beta_7)$ when β_7 is specified to have a log normal distribution, and $\exp(\beta_x)/\exp(\beta_7)$ when both β_x and β_7 are specified to have a log-normal distribution.[11]

While the mixed logit characterizes the distribution of preferences, it does not identify what types of consumers constitute different portions of the distribution. Therefore, we also estimate a latent class logit. The latent class logit is less flexible than the mixed logit, allowing for only discrete or fixed preferences. However, this approach allows us to segment the sample and then estimate preferences separately by segment, facilitating a better identification of which types of consumers have which preferences. Assuming that there are *S* segments in the population, the probability of respondent *n* choosing ride *i* is conditional on the respondent's membership in segment *s*, $\pi_{ni|s}$, where $s = 1,\ldots S$, is as follows:

$$\pi_{ni|s} = \frac{\exp(\boldsymbol{x}_i'\boldsymbol{\beta}_s)}{\sum_{k=1}^{K} \exp(\boldsymbol{x}_k'\boldsymbol{\beta}_s)} \tag{6}$$

We define the latent membership for segmentation as follows:

$$M_{ns}^* = y_n'\lambda_s + \zeta_{ns}, \tag{7}$$

where M_{ns}^* denotes the membership of respondent *n* in segment *s*, y_n is a vector of socioeconomic characteristics, λ_s is a vector of parameters, and ζ_{ns} is an independently distributed Type I extreme value error.

We can then model the probability (π_{ns}) of respondent *n* belonging to segment *s* as follows:

$$\pi_{ns} = \frac{\exp(\boldsymbol{y}_n' \boldsymbol{\lambda}_s)}{\sum_{s=1}^{S} \exp(\boldsymbol{y}_n' \boldsymbol{\lambda}_s)} \tag{8}$$

Finally, the probability of respondent *n* selecting ride *i* (π_{ni}) is the sum of the segments of the probability of the respondent choosing ride *i* conditional on segment membership multiplied by the respondent's probability of segment membership:

$$\pi_{ni} = \sum_{s=1}^{S} \pi_{ns} \pi_{ni|s} \tag{9}$$

5. Results and Discussion

5.1. Summary Statistics

Table 2 presents the summary statistics of the respondent sociodemographics and compares them to census data. The survey sample is reasonably representative in terms of age and race/ethnicity, although it proved fairly difficult to recruit older participants and those of Hispanic, Latino, or Spanish origin. Very low- and high-income households are slightly undersampled, with 35.1% of the sample having an annual household income under $50,000, compared to 38.4% of the national population. The survey sample also overrepresents urban households and underrepresents rural households. Table 3 presents the summary statistics of various questions related to household transport and ride-hailing experience.

Table 2. Respondent sociodemographics and representativeness

	Frequency	Percent	Census Data
Age			
18-24	105	14.0%	11.9%
25-34	120	16.0%	17.9%
35-44	176	23.5%	16.4%
45-54	64	8.5%	16.0%
55-64	120	16.0%	16.6%
65-74	125	16.7%	12.4%
75-84	36	4.8%	6.3%
85 or older	4	0.5%	2.5%
Gender			
Female	390	52.0%	50.8%
Male	358	47.7%	49.2%
Non-binary / third gender	2	0.3%	
Race/Ethnicity			
White	463	61.7%	57.8%
Black or African American	81	10.8%	12.1%
Asian	33	4.4%	5.9%
Hispanic, Latino, or Spanish origin	87	11.6%	18.7%
American Indian or Alaska Native	14	1.9%	0.7%
Middle Eastern or North African	3	0.4%	
Native Hawaiian or other Pacific Islander	3	0.4%	0.2%
Another race or ethnicity not listed above	11	1.5%	0.5%
Multiple	55	7.3%	4.1%
Income			
Less than $15,000	58	7.7%	9.8%
$15,000 to $24,999	69	9.2%	8.3%
$25,000 to $49,999	136	18.1%	20.3%
$50,000 to $99,999	263	35.1%	30.2%
$100,000 to $199,999	183	24.4%	22.9%
$200,000 or more	41	5.5%	8.5%
Location			
Suburban	379	50.5%	52.0%
Urban	278	37.1%	27.0%
Rural	93	12.4%	21.0%
Age, gender, income from 2019 ACS, race/ethnicity from 2020 decennial Census, location from 2017 American Housing Survey			

Source: KAPSARC.

Table 3. Respondent experience (summary statistics)

	Frequency	Percent
Do you or someone in your household own a vehicle that you drive regularly?		
Yes	677	90.3%
No	73	9.7%
Which of the following ride-hailing services have you used in the past?		
Uber	677	90.3%
Lyft	333	44.4%
Other	18	2.4%
In which locations do you use ride-hailing services?		
Around your town or city	495	66.0%
On work trips to other towns or cities	199	26.5%
On vacation to other towns or cities	289	38.5%
Other	19	2.5%
For which types of trips do you use ride-hailing services?		
Commuting to work or school	175	23.3%
For shopping trips	217	28.9%
Going to bars or restaurants	342	45.6%
Going to sports games or concerts	189	25.2%
Getting to or from the airport	366	48.8%
Getting to or from the train station	110	14.7%
Other	62	8.3%
Doctor/hospital/medical appointments	20	2.7%
Car dealer/repair shop	5	0.7%
How do you tend to use ride-hailing services?		
Mostly for trips by yourself	362	48.3%
Mostly for trips with others	250	33.3%
Roughly half the time by yourself and half the time with others	138	18.4%
What is your experience with electric vehicles (EVs)?		
I own an EV.	75	10.0%
I have rented or driven an EV.	86	11.5%
I have ridden in an EV.	176	23.5%
I am interested in EVs.	281	37.5%
I do not like EVs.	56	7.5%
I do not know much about EVs.	231	30.8%
Have you heard of autonomous vehicles or self-driving cars?		
Yes	656	87.5%
No	78	10.4%
Unsure	16	2.1%

Source: KAPSARC.

The survey took an average of seven minutes and a median of six minutes to complete. Importantly, the respondents mostly perceived the survey as consequential, with 82.1% of them answering that they believe that the trip choices made by themselves and other respondents in the survey would somewhat, probably, or definitely, be taken into consideration by transportation planners and policy makers.

5.2. Price Elasticity of Demand

The respondents took an average of 4.4 trips per month, with a median of 2 and a standard deviation of 6.6.[12] The respondents were asked, "If ride-hailing services were cheaper, costing about half of what they currently do, how much more would you use them?" Based on this information, we could perform a back-of-the-envelope calculation of the price elasticity of demand for ride-hailing trips using the following formula:

$$PED = \frac{\frac{trips\_per\_month\_2 - trips\_per\_month}{0.5*(trips\_per\_month\_2 + trips\_per\_month)}}{0.5}, \qquad (10)$$

where *trips_per_month* is the respondent's stated number of current trips per month and *trips_per_month_2* is the respondent's anticipated number of trips after the 50% price decrease.[13] We found that demand for ride-hailing trips is elastic, with a mean *PED* of 1.39 and a median of 1.33.

5.3. Mixed Logit Model

Table 4 displays the results of estimating the mixed logit model on the choice experiment data from the survey.[14]

Table 5 shows associated WTP estimates calculated using the ratio of the coefficients described in Section 4. The coefficients of price, the number of stops, and the ride time are negative, as expected. The large and significant standard deviation of the number of stops coefficient indicates heterogeneity in this attribute, while the small and mostly insignificant standard deviation of the ride time coefficient suggests similar preferences across the respondents. The autonomous and driverless coefficients are all negative and significant, suggesting that disutility is associated with autonomous technology and is even more strongly associated with driverless vehicles. In some cases, the respondents appear to have a slight preference for HEVs but no significant preference for EVs. Table 5 shows that the respondents are willing to pay $1.33-$6.86 to avoid an additional stop to pick up another passenger.[15] They are willing to pay $0.55-$1.06 for a one-minute reduction in ride time. The respondents are willing to pay $1.90-$3.58 to avoid riding in an AV and $8.43-$12.49 to avoid riding in a driverless vehicle. They are willing to pay $1.29-$2.22 to ride in an HEV as opposed to an ICE vehicle. Take together, these results show that while the respondents are averse to longer ride times and more carpooling stops, they are an order of magnitude more averse to riding in a driverless car. Furthermore, the WTP for an environmentally cleaner vehicle, such as an HEV or an EV, is minimal.

Table 4. Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
Mean						
Price ($)	-2.961***	-2.927***	-2.738***	-2.648***	-2.336***	-2.400***
	(0.333)	(0.353)	(0.328)	(0.271)	(0.214)	(0.266)
Number of Stops	-0.355***	-2.076***	-2.168***	-2.181***	-2.051***	-1.987***
	(0.036)	(0.338)	(0.347)	(0.394)	(0.394)	(0.431)
Ride Time (minutes)	-0.0549***	-0.0451***	-0.0502***	-2.993***	-2.925***	-2.845***
	(0.010)	(0.011)	(0.011)	(0.215)	(0.389)	(0.216)
Autonomous	-0.152***	-0.192***	-0.200***	-0.198***	-0.184**	-0.184***
	(0.053)	(0.057)	(0.060)	(0.059)	(0.072)	(0.064)
Driverless	-0.646***	-0.659***	-0.673***	-0.673***	-0.815***	-0.844***
	(0.058)	(0.061)	(0.062)	(0.062)	(0.077)	(0.081)
HEV	0.115**	0.096	0.098	0.101	0.112	0.117*
	(0.057)	(0.062)	(0.063)	(0.062)	(0.081)	(0.069)
EV	0.019	0.020	0.022	0.024	0.023	0.028
	(0.058)	(0.064)	(0.065)	(0.065)	(0.084)	(0.072)
Standard Deviation						
Price ($)	1.292***	1.034***	0.857***	0.751***	0.477***	-0.662***
	(0.263)	(0.230)	(0.257)	(0.229)	(0.160)	(0.226)
Number of Stops		2.292***	2.477***	2.427***	2.070***	2.307***
		(0.362)	(0.357)	(0.382)	(0.327)	(0.456)
Ride Time (minutes)				0.308	0.846	-0.546**
				(0.446)	(0.794)	(0.259)
Autonomous			0.436***	0.434***	-0.177	-0.190
			(0.126)	(0.118)	(0.229)	(0.219)
Driverless					1.162***	1.175***
					(0.098)	(0.095)
HEV						0.329**
						(0.162)
Observations	8,564	8,564	8,564	8,564	8,564	8,564
AIC	5,349	5,245	5,249	5,250	5,152	5,152
BIC	5,406	5,309	5,320	5,327	5,236	5,244

Robust standard errors in parentheses are clustered at the respondent level. When included as random variables, price, ride time, and number of stops are specified to have log-normally distributed coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Source: KAPSARC.

Table 5. Willingness to pay (per ride)

Number of Stops	-$6.86	-$2.34	-$1.77	-$1.60	-$1.33	-$1.51
Ride Time (minutes)	-$1.06	-$0.84	-$0.78	-$0.71	-$0.55	-$0.64
Autonomous	-$2.94	-$3.58	-$3.09	-$2.80	-$1.90	-$2.03
Driverless	-$12.48	-$12.30	-$10.40	-$9.51	-$8.43	-$9.30
HEV	$2.22					$1.29
WTP estimates are based on results from Table 3 and are only calculated for parameters with statistically significant coefficients.						

Source: KAPSARC.

We include interactions between the ride time coefficient and the number of stops, driverless, and autonomous coefficients. The results are presented in Table 6. The interaction between the number of stops and ride time in column 3 is significant. Calculating the ratio of the number of stops and price coefficients (as explained in Section 4) results in a WTP of −$2.33 per stop. The interaction coefficient of the number of stops * ride time implies an additional WTP of $0.02 per minute per stop. This result suggests that as the ride time increases, the absolute value of the negative WTP per stop decreases by $0.02 per minute, meaning that additional stops are considered less bothersome when the ride is longer. However, as the ride time decreases, the negative WTP per stop becomes $0.02 less (or greater in absolute value) per minute, meaning that additional stops are considered more bothersome when the ride is shorter.

The interactions between the driverless and ride time coefficients in columns 5 and 8 are negative and statistically significant, showing that as ride time increases, the WTP for driverless (approximately −$7) becomes even lower (reduced by $0.05-0.06 per minute). This finding implies that riders are more averse to driverless cars the longer the ride is. However, as the ride time decreases, the WTP for a driverless car becomes less negative, meaning that riders are less averse to driverless cars on shorter trips. Indeed, when we split the sample by the long- and short-ride scenarios and estimate the same specification as column 5 of Table 4 separately for each subsample, our results imply a WTP for a driverless ride of −$3.53 for short rides and −$23.32 for long rides.

Table 6. Heterogeneity in ride-hailing preferences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean								
Price ($)	-3.227***	-2.533***	-2.476***	-2.930***	-2.341***	-2.953***	-2.325***	-2.294***
	(0.499)	(0.313)	(0.227)	(0.318)	(0.229)	(0.336)	(0.200)	(0.206)
Number of Stops	-0.393***	-1.648***	-1.628***	-0.350***	-2.108***	-0.356***	-2.026***	-2.048***
	(0.047)	(0.453)	(0.293)	(0.036)	(0.380)	(0.036)	(0.402)	(0.396)
Ride Time (minutes)	-0.0563***	-2.816***	-2.772***	-0.0562***	-2.953***	-0.0553***	-2.891***	-2.840***
	(0.010)	(0.212)	(0.190)	(0.010)	(0.343)	(0.010)	(0.329)	(0.328)
Autonomous	-0.167***	-0.202***	-0.201***	-0.151***	-0.186***	-0.168**	-0.210**	-0.282***
	(0.054)	(0.066)	(0.064)	(0.053)	(0.068)	(0.081)	(0.097)	(0.101)
Driverless	-0.632***	-0.828***	-0.804***	-0.577***	-0.690***	-0.646***	-0.815***	-0.654***
	(0.059)	(0.082)	(0.079)	(0.077)	(0.103)	(0.058)	(0.077)	(0.104)
HEV	0.102*	0.102	0.102	0.117**	0.103	0.116**	0.117	0.119
	(0.059)	(0.071)	(0.069)	(0.057)	(0.074)	(0.058)	(0.078)	(0.079)
EV	0.006	0.012	0.011	0.020	0.016	0.020	0.028	0.034
	(0.059)	(0.075)	(0.071)	(0.058)	(0.078)	(0.058)	(0.081)	(0.082)
Number of Stops * Ride Time	0.002	0.003	-6.376***					
	(0.002)	(0.002)	(0.649)					
Driverless * Ride Time				-0.003	-0.00455*			-0.00581**
				(0.002)	(0.003)			(0.003)
Autonomous * Ride Time						0.001	0.001	0.004
						(0.002)	(0.003)	(0.003)
Standard Deviation								
Price ($)	1.471***	-0.707***	-0.472***	1.271***	0.480***	1.284***	0.476**	0.456***
	(0.373)	(0.238)	(0.136)	(0.249)	(0.112)	(0.267)	(0.195)	(0.142)
Number of Stops		1.998***	1.982***		2.081***		2.068***	2.075***
		(0.512)	(0.261)		(0.329)		(0.301)	(0.307)
Ride Time (minutes)		-0.574**	0.400**		0.938**		0.788	0.788
		(0.236)	(0.194)		(0.447)		(0.677)	(0.607)
Autonomous		-0.216	0.160		-0.180		-0.173	-0.173
		(0.194)	(0.258)		(0.237)		(0.233)	(0.238)
Driverless		1.177***	1.146***		1.169***		1.160***	1.166***
		(0.096)	(0.094)		(0.097)		(0.098)	(0.098)
HEV		0.336**	0.289					
		(0.158)	(0.198)					
Number of Stops * Ride Time			1.278***					
			(0.265)					
Observations	8,564	8,564	8,564	8,564	8,564	8,564	8,564	8,564
AIC	5,349	5,153	5,146	5,350	5,150	5,351	5,153	5,151
BIC	5,413	5,252	5,252	5,413	5,242	5,415	5,245	5,249

Robust standard errors in parentheses are clustered at the respondent level. When included as random variables, price, ride time, number of stops, and number of stops interacted with ride time are specified to have log-normally distributed coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Source: KAPSARC.

Table 7 shows responses to some of the post-choice-experiment debriefing questions, which are intended to help us understand the respondents' choices. The most prevalent concern about AVs is safety, followed by the specific concern about not having a driver to handle emergency situations (in driverless vehicles). More respondents would enjoy having a driver to chat with than not (22.1% vs. 14.7%). Despite the general aversion to driverless vehicles, a quarter of the respondents would like to ride in such a vehicle out of curiosity, and just over 10% would like to ride in a driverless vehicle because it is more fuel efficient and has better performance.

A larger share of respondents wish to ride in an EV either out of curiosity (47.5%) or because EVs are good for the environment (38.9%). Less than 15% do not trust EV technology. Nevertheless, this openness to EVs does not translate into a significant WTP for EVs in the choice experiment. The most prevalent opposition to carpooling is not wanting to ride with a stranger (40.9%), followed by safety concerns (36.8%) and concerns about longer ride times (28.9%).

Table 7. Ride-hailing attitudes (summary statistics)

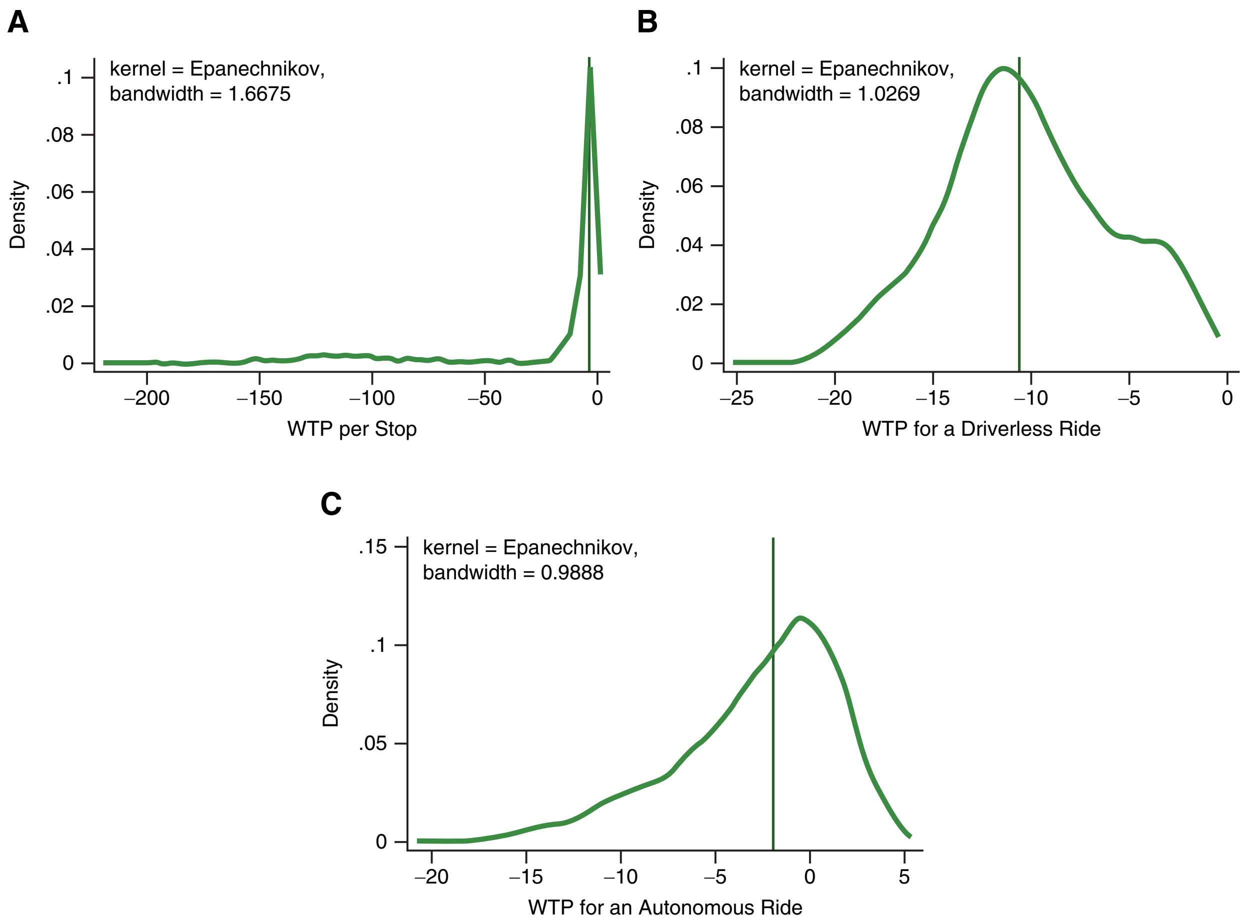
	Frequency	Percent
Regarding ride-hailing in driverless vehicles, with which of the following do you agree?		
I have safety concerns about self-driving vehicles.	459	61.2%
I would be concerned if there is no driver to handle emergency situations.	396	52.8%
I do not trust self-driving technology.	263	35.1%
I enjoy having a driver to chat with.	166	22.1%
I'd prefer not to have to chat with a driver.	110	14.7%
I would like to ride in one because I'm curious about them.	190	25.3%
I would like to ride in one because they operate more fuel efficiently.	88	11.7%
I would like to ride in one because they have better performance (e.g., smoother ride).	83	11.1%
Regarding ride-hailing in electric vehicles, with which of the following do you agree?		
I do not trust EV technology.	108	14.4%
I am worried an EV would run out of electricity, leaving me stranded.	227	30.3%
I would like to ride in an EV because I am curious about them.	356	47.5%
I would like to ride in an EV because they are eco-friendly.	292	38.9%
Regarding carpooling (pick up an additional rider) while ride-hailing, with which of the following do you agree?		
Carpooling makes trips take too much time.	217	28.9%
I do not want to ride with a stranger.	307	40.9%
Carpooling with strangers could be dangerous.	276	36.8%
I generally don't mind riding with a stranger, but you never know who the passenger will be, and he/she might bother me in some way.	238	31.7%
I would enjoy meeting new people this way.	116	15.5%
I'd often be willing to carpool if it makes my ride substantially cheaper.	134	17.9%

Source: KAPSARC.

To further explore the WTP for ride attributes, we can estimate the elements in the coefficient covariance matrix from column 3 of Table 5 (i.e., allowing for correlation across parameters). We can then calculate respondent-level preference parameters following Revelt and Train (2000). Finally, we plot kernel density estimates of the distribution of respondent-level preferences. The results are shown in Figure 2, with vertical red lines representing the median WTP. Figure 2a displays the distribution of the coefficient of the number of stops. The median WTP per additional stop is −$3.66. There is a large mass of respondents with a relatively low WTP for an additional stop but a very long left tail with a mean of −$23.45, suggesting that a small number of respondents are highly averse to carpooling.

Figure 2b displays the distribution of the driverless coefficient. The median WTP is −$10.59; all respondents have a negative coefficient, and the distribution is fairly symmetric. In other words, with all else being equal, all respondents prefer not to ride in a driverless car, with the WTP to avoid a driverless ride being roughly normally distributed around a mean of $10.15 and a standard deviation of $4.29. Figure 2c shows the distribution of the autonomous coefficient. The median WTP to avoid a ride with autonomous or self-driving technology is $1.92. However, approximately 30% of the respondents actually have a positive WTP to ride in such a vehicle. This finding suggests that with the condition of having a driver in the car, many riders are not opposed to self-driving technology.

Figure 2. Distributions of individual preference parameters



Source: KAPSARC.

5.4. Latent Class Logit Model

We first estimate latent class logits, assuming that 2, 3, and 4 different classes exist. Table 8 shows the Akaike information criterion (AIC), consistent AIC (CAIC), and Bayesian information criterion (BIC) for each model. While the AIC is smallest for a 4-class model, both the CAIC and BIC are minimized in the 3-class model. Therefore, we can proceed with the analysis of the 3-class model.

Table 8. Latent class logit model fit.

Classes	LL	N parameters	AIC	CAIC	BIC
2	−2,602	15	5,234	5,319	5,304
3	−2,529	23	5,104	5,233	5,210
4	−2,514	31	5,091	5,265	5,234

Source: KAPSARC.

Table 9 presents the results of the 3-class latent class logit model and the results of the jointly estimated class membership model. Class 1 is willing to pay $3.72 to avoid an additional carpooling stop and $0.83 for each reduced minute of ride time. Those in class 1 are willing to pay an additional $1.43 to ride in an HEV, although this result is statistically significant at only the 10% level. Notably, they do not have a significant negative preference for autonomous or driverless cars. Lower-income households are somewhat more likely to belong to this class, although the membership variable is only marginally significant. Perhaps the increased price sensitivity of this class makes those who belong to it less opposed to self-driving technology if and when they receive a discount for such rides. In contrast, respondents who identify as politically conservative (versus liberal or neither) are less likely to belong to this class. More liberal respondents are perhaps more in favor of environmentally friendly technologies, which may drive the WTP for HEVs.

The respondents in class 2 are less price sensitive than are those in class 1. They are willing to pay $0.47 for each reduced minute of ride time. While they do not have a significant preference for AV technology, they are willing to pay $2.77 to avoid a driverless ride. They are also willing to pay more ($2.65) to ride in an HEV. Much like class 1, lower-income and nonconservative respondents are more likely to belong to this class. Furthermore, respondents who live in an urban area are considerably more likely to belong to class 2. This finding may drive the difference in driverless preferences between classes 1 and 2. For example, respondents in urban areas may be more concerned about the safety of driverless cars, given their denser built environment and greater traffic congestion.

The respondents in class 3 are less likely to be low income, less likely to live in urban areas, and more likely to identify as politically conservative. They have strong negative preferences for autonomous and driverless rides and for rides in HEVs and EVs. However, given the imprecisely estimated price coefficient, we are unable to calculate the WTP for these attributes. It is likely that this population constitutes the left tails of the autonomous and driverless coefficient distributions in Figures 2b and 2c.

Table 9. Latent class logit and class membership.

Variables	Class 1	Class 2	Class 3	Share 1	Share 2	Share 3
Price ($)	−0.329 (0.079)***	−0.0856 (0.020)***	−0.064 (0.075)			
Number of stops	−1.223 (0.247)***	−0.053 (0.060)	−0.717 (0.186)***			
Ride time (minutes)	−0.274 (0.071)***	−0.0406 (0.014)***	−0.012 (0.048)			
Autonomous	−0.130 (0.254)	−0.066 (0.080)	−0.885 (0.234)***			
Driverless	−0.217 (0.202)	−0.237 (0.086)***	−3.616 (0.631)***			
HEV	0.470 (0.275)*	0.227 (0.085)***	−0.955 (0.336)***			
BEV	0.181 (0.264)	0.081 (0.083)	−0.578 (0.255)**			
Income: < $50k				0.620 (0.374)*	0.893 (0.347)**	0.000
Urban				0.415 (0.303)	0.748 (0.281)***	0.000
Conservative				−0.568 (0.286)**	−0.445 (0.264)*	0.000
Constant				0.130 (0.242)	0.504 (0.234)**	0.000
Observations	8,564	8,564	8,564	8,564	8,564	8,564
Number of groups	4,282	4,282	4,282	4,282	4,282	4,282
Membership share (%)				27.3	50.3	22.4

Notes:

** $p < 0.1$.*

*** $p < 0.05$.*

**** $p < 0.01$.*

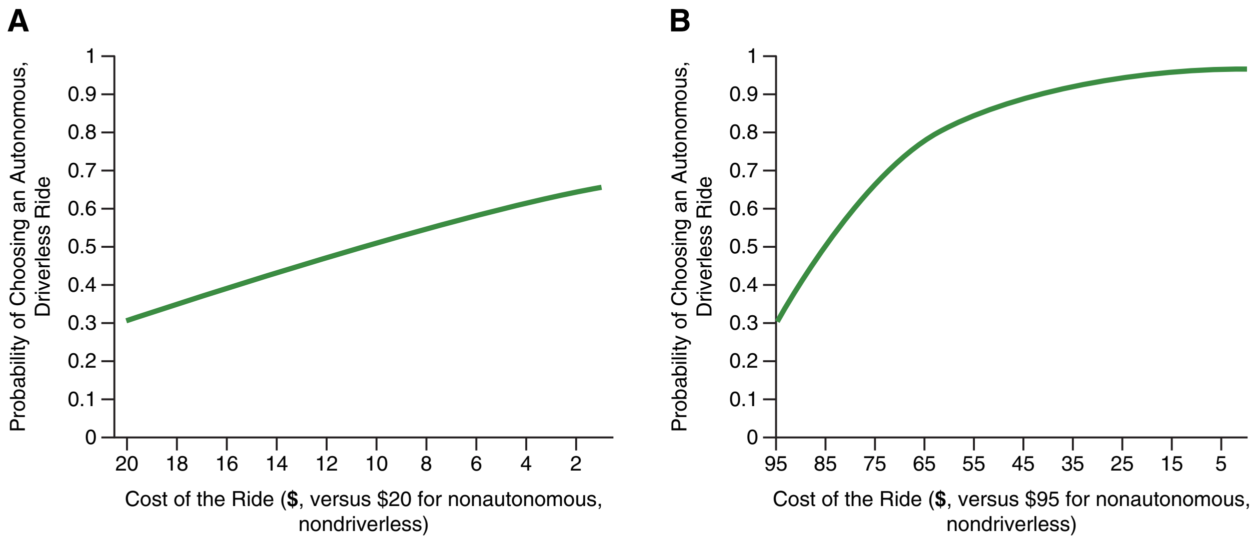
Robust standard errors in parentheses are clustered at the respondent level.

Source: KAPSARC.

5.5. Simulations

We performed several simulations to further investigate the tradeoffs that riders make between ride characteristics. These simulations utilized the coefficients estimated in column 6 of Table 4 to estimate the probabilities of riders choosing two alternative rides. In the first simulation, riders choose between a 10-minute trip with no carpooling in a non-HEV and a non-EV that is 1) autonomous and driverless and 2) nonautonomous and with a driver. When both rides cost $20, 30.8% of the riders choose the driverless ride. We then hold the cost of ride 2 constant at $20 and decrease the cost of the driverless ride by $1 increments, showing how this discount increases the probability of respondents choosing the driverless ride. The results are shown in Figure 3a. With all else being equal, the average rider prefers to ride with a driver and requires a discount to ride in a driverless car. Even when the driverless ride costs a fraction of the original $20 price, only approximately two-thirds of riders will choose it. Figure 3b displays similar results but for a longer journey of 50 minutes with a baseline cost of $95. With a reduction in price from $95 to $65, the probability of choosing the driverless ride sharply increases from approximately 30% to almost 80%, but it then starts to plateau with further discounting.

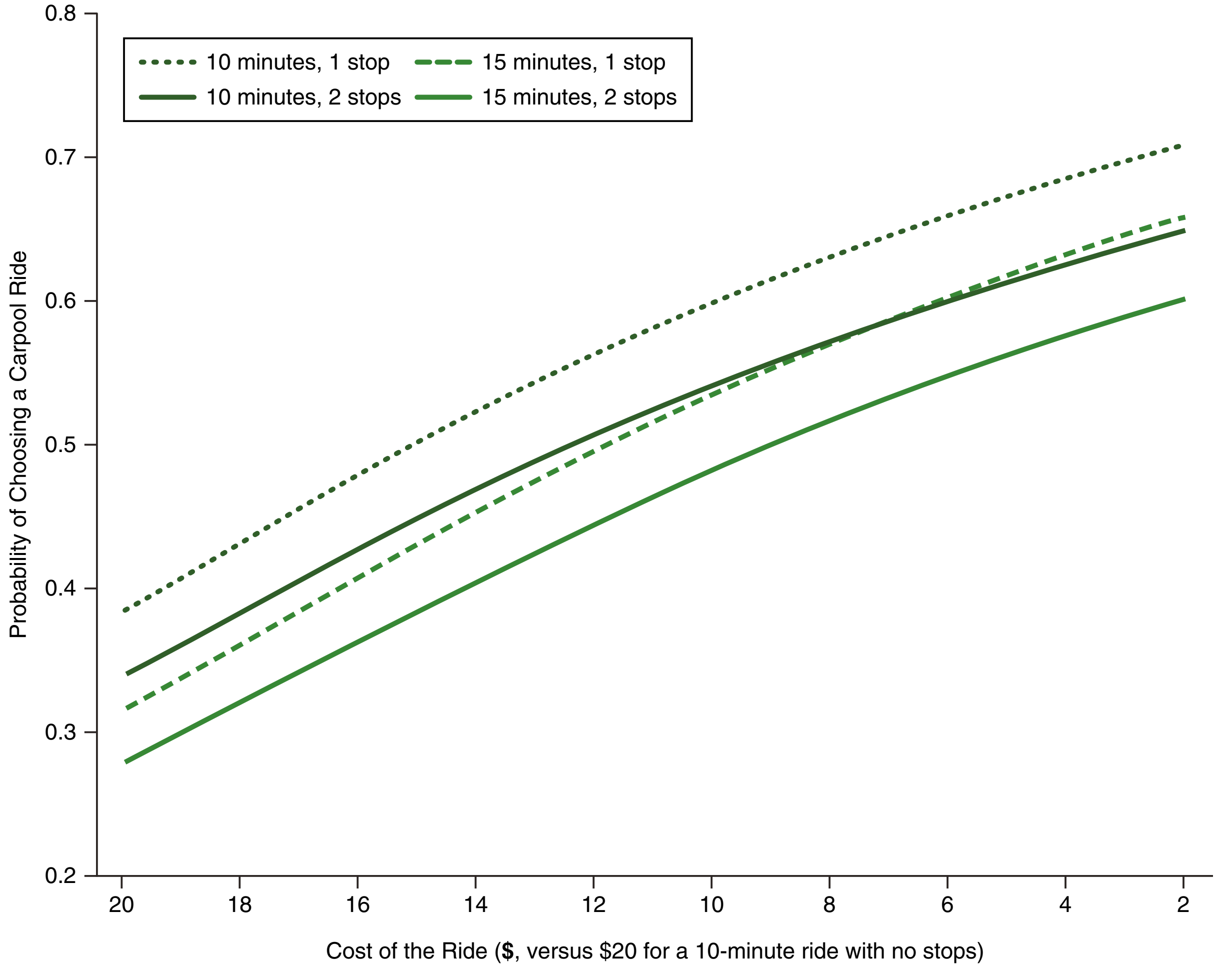
Figure 3. Probability of choosing an autonomous/driverless ride



Source: KAPSARC.

The second simulation compares the probability of choosing four different rides with carpooling versus the same ride without carpooling. All rides are in nonautonomous, non-HEV, non-EV cars with a driver. The ride without carpooling is 10 minutes and costs $20. The carpool rides are 1) 10 minutes with one stop, 2) 15 minutes with one stop, 3) 10 minutes with two stops, and 4) 15 minutes with two stops. As the cost of these rides decreases from $20, we predict the probability of choosing each ride versus the noncarpool ride. The results are shown in Figure 4. The blue line shows that, all else being (including the ride time) equal, the carpool ride requires a discount of $5 (cost of $15 versus $20) to make the average rider indifferent between the one-stop carpool and the noncarpool ride. The gray line indicates that a discount of $8 is needed to make the average rider indifferent between the two-stop carpool and the noncarpool rides. In other words, even if the ride with the carpool does not increase the ride time, consumers still require a discount to compensate them for the disutility of carpooling. Factoring in a longer ride time from carpooling lowers the probability of choosing these rides. Adding one more stop (blue line vs. gray line) reduces the utility by less than adding five minutes to the ride (blue line to orange line).

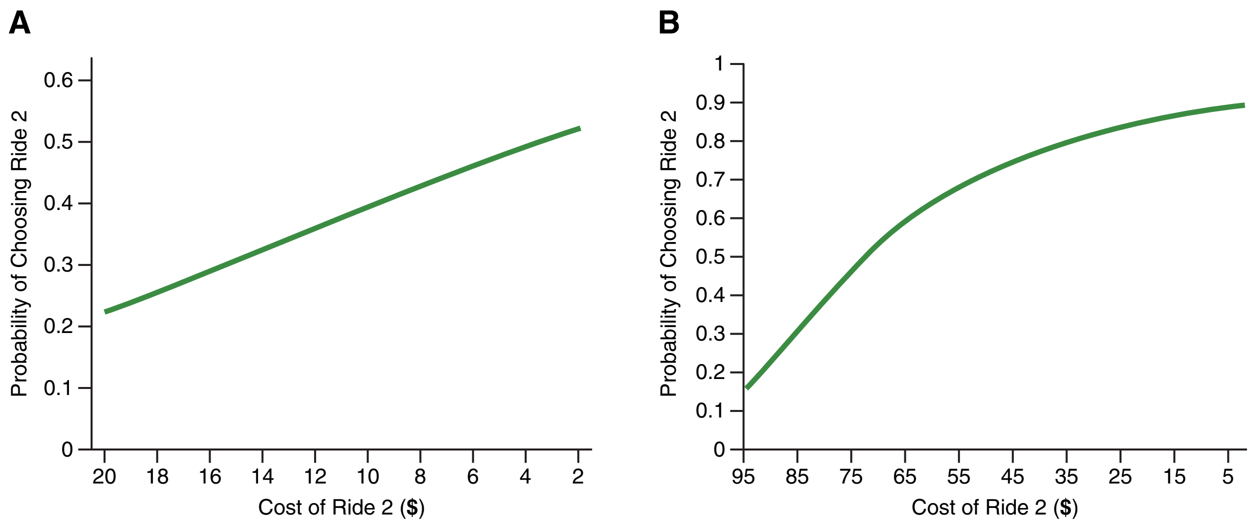
Figure 4. Probability of choosing carpooling



Source: KAPSARC.

The third simulation investigates the probability of choosing a shared, driverless, and electric ride versus a conventional ride. Specifically, we compare the probability of choosing an autonomous, driverless ride in an EV with one carpooling stop, which takes 20% longer, to that of choosing a nonautonomous, nondriverless ride in an ICE vehicle with no carpooling. The results are shown in Figure 5. In Figure 5a, we assume a shorter and less expensive ride, and in Figure 5b, we assume a longer and more expensive ride. Figure 5a shows that for the shorter ride, the shared, driverless, and electric ride would need to cost only $3 for riders to be indifferent between it and the $20 conventional ride. Figure 5b shows that for the longer ride, the shared, driverless, and electric ride would need to cost approximately $73 for riders to be indifferent between it and the $95 conventional ride.

Figure 5. Probability of choosing a shared, driverless, and electric ride



Source: KAPSARC.

In Figure 5a, Ride 2 is in an autonomous, driverless EV that makes one stop for carpooling and has a 12-minute drive time. The probability of choosing Ride 2 is compared to the probability of choosing Ride 1, which is in a nonautonomous ICE vehicle with a driver and no carpooling that takes 10 minutes and costs $20.

In Figure 5b, Ride 2 is in an autonomous, driverless EV that makes one stop for carpooling and has a 60-minute drive time. The probability of choosing Ride 2 is compared to the probability of choosing Ride 1, which is in a nonautonomous ICE vehicle with a driver and no carpooling that takes 50 minutes and costs $95.

6. Conclusion

Our results suggest that despite the theoretical potential for emission reductions from shared, autonomous, and electric ride-hailing, this future vision of transport faces substantial barriers from a consumer behavior perspective. First, most passengers do not want to share a ride with strangers, with some requiring significant discounts to do so. The primary barrier is simply that respondents do not want to ride with strangers, followed by safety concerns. Second, riders are even more averse to riding in a driverless car, citing safety as their main concern. However, the resistance appears to be to not having a driver rather than the self-driving technology itself. Third, while most riders are open to riding in HEVs or EVs, they are generally not willing to pay a higher price to ride in these lower-emission vehicles.

We find that riders are more opposed to additional stops on shorter trips. Given the greater potential for passenger pickup and destination matching in urban areas, this opposition will further limit the wider adoption of carpooling. Our latent class analysis shows that nonurban and more politically conservative respondents are more likely to have left-tail preferences for AVs and driverless vehicles.

Overall, the promise of lower costs for shared, autonomous rides does not appear to overcome riders' opposition to carpooling and driverless cars. One simulation shows that even when a short driverless ride costs only a fraction of the (otherwise same) ride with a driver, only two-thirds of riders will choose it. Another simulation shows that the average rider is indifferent between choosing a $20 ride with no carpooling and choosing a $15 ($12) ride with one (or two) stop(s) when the ride time is held constant. To the extent that carpooling increases the ride time, which is most likely the case, greater discounts are then required.

Putting the pieces together in our final simulation, we find that the average rider requires an approximately $20 discount for a shared, autonomous, and electric ride versus a conventional ride. While such a discount may be more realistic for a longer ride with a higher price point, it seems unlikely that cost reductions from automation and carpooling would be sufficient to offer enough of a discount for shorter trips.

Our findings highlight two major barriers to the shared, autonomous, electric MOD future, the first of which is safety concerns. These concerns could potentially be alleviated by a robust regulatory framework, as well as proof of concept by the industry. The second barrier is an aversion to riding with strangers. This barrier could also be partially addressed with regulations offering consumer protections, as well as information campaigns designed to create and bolster social norms (e.g., encouraging sharing and the exhibition of polite behavior such as maintaining personal space).

Endnotes

[1] https://www.uber.com/newsroom/10000-cities/

[2] https://blog.olacabs.com/know-where-ola-is-resuming-its-services/

[3] https://techcrunch.com/2021/03/29/didi-chuxing-expands-to-south-africa-to-take-on-bolt-and-uber/

[4] https://www.pewresearch.org/fact-tank/2019/01/04/more-americans-are-using-ride-hailing-apps/

[5] Qualtrics, a professional survey company, was contracted to administer the survey. It recruited respondents using its online panel and provided financial compensation as an incentive. Quotas were set to ensure the national representativeness of the sample.

[6] Specifically, the consequentiality statement read as follows: “Your answers may be used to help state and local policy makers in their transportation planning.”

[7] Of the 1,783 respondents who went to the starting page of the survey, 1,003 were screened out for not having ever used a ride-hailing service (922), not agreeing to the consent form on the first page (67), or being younger than 18 years of age (14). Thirty did not complete the survey, and the remaining 750 constitute our sample.

[8] The attributes were based on prior studies (Lavieri and Bhat 2019; Sweet 2021) and were chosen to convey the options in a simple and easy-to-understand manner. The attributes were limited to five, including price, to limit the complexity and cognitive burden of the choice task.

[9] Lloyd-Smith, Adamowicz, and Dupont (2019) find that asking a question about perceived consequentiality prior to a valuation question reduces the number of survey respondents who perceive the survey as inconsequential. Our consequentiality question read as follows: “To what extent do you believe the trip choices made by you and other survey respondents in the following questions will be taken into consideration by transportation planners and policy makers?” Over four-fifths of the respondents indicated that they believe that their choices would somewhat, probably, or definitely be taken into consideration by transportation planners and policy makers.

[10] Two options (plus the “status quo” of, in this case, the option to select neither ride) are the standard for most choice experiments in environmental economics (Oehlmann et al. 2017). More options increase complexity and cognitive burden, and there is evidence that two alternatives plus a status quo option are associated with a better choice model fit (Rolfe and Bennett 2009).

[11] We are unable to estimate parameters in the WTP space because in the majority of specifications, the log-likelihood functions do not converge to a well-defined maximum value.

[12] This was based on a fill-in-the-blank question with an “unsure” option. If “unsure” was selected, the respondent was asked to select one of a few options: every day, a few times a week, a few times a month, or a few times a year or less. For these four options, we assumed 25.8 (6 times a week times 4.3 weeks per month), 12.9 (3 times a week times 4.3 weeks per month), 3, or 0.17 (2 times a year divided by 12 months) trips per month.

[13] For respondents who indicated they would ride "twice as much" as they currently do, trips_per_month_2 is double trips_per_month. For those who selected "a few more times a week," "a few more times a month," or "a few more times a year," trips_per_month_2 is trips_per_month plus 12.9 (3 times a week times 4.3 weeks per month), plus 3, or plus 0.17 (2 times a year divided by 12 months), respectively.

[14] STATA 17 software was used for all model estimations. In Tables 4, 6, and 9, the first row is a header labeling the columns. In Tables 4 and 6, each column represents a different model specification and is estimated separately. In Table 9, all parameters in the table are jointly estimated. The tables present estimated coefficients with standard errors in parentheses below, with the significance of the estimated p values indicated with asterisks.

[15] This estimate is close to that of Sweet (2021), who estimates that a discount of $1-$4 is required for a passenger to share a ride.

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Appendix

Table A1. Other attitudinal variables (summary statistics)

	Frequency	Percent
I usually try new products before other people do.		
Strongly agree	163	21.7%
Somewhat agree	223	29.7%
Neither agree nor disagree	152	20.3%
Somewhat disagree	148	19.7%
Strongly disagree	64	8.5%
I like to be the first among my friends and family to try something new.		
Strongly agree	163	21.7%
Somewhat agree	205	27.3%
Neither agree nor disagree	172	22.9%
Somewhat disagree	153	20.4%
Strongly disagree	57	7.6%
I like to tell others about new brands or technology.		
Strongly agree	196	26.1%
Somewhat agree	248	33.1%
Neither agree nor disagree	157	20.9%
Somewhat disagree	90	12.0%
Strongly disagree	59	7.9%
Which of the following best describes your political ideology?		
Conservative	219	29.2%
Liberal	198	26.4%
Moderate	333	44.4%
How important are environmental issues to you personally?		
Extremely important	177	23.6%
Very important	205	27.3%
Moderately important	207	27.6%
Slightly important	124	16.5%
Not at all important	37	4.9%
How important is it for the USA to take steps now to reduce greenhouse gas emissions?		
Extremely important	227	30.3%
Very important	210	28.0%
Moderately important	156	20.8%
Slightly important	114	15.2%
Not at all important	43	5.7%

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About the Project

We offer the most comprehensive analysis to date of global plug-in electric vehicle (PEV) subsidies. We accomplish this by estimating vehicle choice models for 23 countries using 2010–2019 sales data and using counterfactual simulations to assess the cost-effectiveness of PEV incentives.

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