User Decision-Making and Technology Choices
in the U.S. Carsharing Market

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Abstract

Each time a user of a carsharing service reserves a vehicle they commonly choose from a selection of available vehicles that vary in a range of attributes including rental price, the distance of the vehicle from their current location, the availability of the vehicle at their desired reservation time, and the type of vehicle (e.g. gasoline, hybrid or electric). In this paper we analyze the results of an online discrete choice survey administered to members of a leading North American carsharing organization. We quantify how carsharing users value price, distance from them, availability at the desired time and vehicle type. We find that for an average user obtaining a vehicle when and where they want it is of greatest importance. Traveling one mile for a vehicle or rescheduling a trip by up to one hour are each worth approximately \$2/hour in vehicle price. Users who report driving longer distances are increasingly less likely to choose either a plug-in hybrid or fully electric vehicle. Additionally, we find that carsharing acts as a conduit to introduce users to new vehicle technology: more than half users report having driven a hybrid vehicle through carsharing, more than 400 users for every one hybrid vehicle in service.

Keywords: carsharing; decision-making; hybrid vehicles; electric vehicles; discrete choice; logit model; preferences; shared mobility

1 Introduction

The U.S. market for carsharing has grown steadily over the past decade, with nearly one million users renting vehicles on a short-term basis from 25 operators (TSRC 2013). In this study we focus on round-trip carsharing, a leading carsharing business model in which users rent cars for increments of one hour and up, returning the vehicle to the original pick up location at the end of their rental. In such services, users commonly choose from a range of available vehicles when they make a reservation, trading off a range of attributes including the hourly price of the vehicle, the distance they must travel to access the vehicle and the time the vehicle is available, as well of the characteristics of the vehicle itself, including make, model and body style. For example, a user may have to choose between the vehicle they want that is only available at a time later than they desire, or a vehicle that is available at the time requested but further away. For many years members of round-trip carsharing services have been able to choose from a wide range of gasoline and hybrid-electric vehicles (HEVs). More recently, advanced technologies including plug-in hybrid-electric vehicles (PHEVs) and battery-electric vehicles (BEVs) have been introduced into some carsharing fleets, incentivized in California with the ability to earn bonus credits under the Zero Emissions Vehicle (ZEV) mandate (CARB 2012), providing carsharing users additional vehicle choices. Understanding how carsharing users make decisions about which shared vehicle they will reserve, if any, is essential for the effective management of carsharing services and the overall appeal of carsharing relative to other transportation modes.

The emerging literature on carsharing has considered a range of issues including the demographics of carsharing users, factors influencing the success of carsharing schemes, the impact of carsharing on vehicle ownership and vehicle miles traveled (VMT), and the relationship between carsharing and other transportation modes. In particular, several papers have investigated factors that contribute to overall levels of carsharing usage. Stillwater et al. (2009) investigate the attributes of the urban environment that influence the usage rates of carsharing vehicles, using aggregate reservation data from a single carsharing service. Barnes and Rutherford (2001) use a logit model to estimate the influence of various carsharing service attributes on the likelihood of prospective members joining carsharing. Membership fees and usage fees are found to be important, but access distance and reserve time were not found to be significant. Cervero et al. (2006) surveyed City CarShare users in San Francisco, finding that car type was an important factor in vehicle choice for more than half of the users surveyed. Catalano et al. (2008) surveyed travelers in Palermo, Italy, about travel preferences and mode choice (including carsharing) as a function of cost and time. More recently, de Lorimier and El-Geneidy (2013) used a regression approach, finding that vehicle age and proximity to users are important decision factors.

However, the carsharing literature has not yet considered reservation decision-making from the perspective of individual users, capturing the influence of operational attributes such as the location of the vehicle relative to the user, and the availability of the vehicle at the time desired by the user.

In contrast with the extensive literature on consumer purchasing of alternative fuel vehicles in the light duty vehicle fleet (reviewed by Al-Alawi and Bradley (2013)), little has been written about the role of vehicle powertrain technologies in the carsharing context. An early study by Rutherford (2003) noted that vehicles in the Flexcar program were at the time 50% more fuel-efficient than the average new vehicle sold in the U.S., and stated the goal of incorporating alternative fuel vehicles. In Europe carsharing operators incorporated electric vehicles as early as the 1970s and several EV-based sharing systems (e.g. Car2Go, Autolib) are in operation today. However, these systems are typically based on a single vehicle type and consumers simply choose the closest available vehicle, conflating service and vehicle attributes. The re-introduction of PHEVs and BEVs into the U.S. market by automakers in late 2010 has provided the opportunity to use these alternative fuel vehicles in carsharing fleets. Levine et al. (2014) incorporated vehicle type as a choice attribute but did not find it to be statistically significant. According to a tweet from the Car Sharing Association's conference in September, 2013 "RT @AutoShare: Half the people in San Francisco Bay Area who have driven electric cars did so thru @CityCarShare. #carsharing13." This anecdote suggests a potentially important role for carsharing in the broader adoption of alternative fuel vehicles in the U.S. light duty vehicle fleet, providing opportunities for drivers to readily trial new technologies and observe new technologies in use, key determinants of the rate of technology adoption (Rogers, 2003).

With this study we aim to make two contributions to carsharing literature. First, we seek to understand the relative importance carsharing users place on key carsharing service attributes such as price, distance and time. Second, given the increasing interest in carsharing applications for alternative fuel vehicles, we investigate both the rate of exposure of carsharing users to new vehicle technologies through carsharing, and the willingness of users to drive hybrid-electric (HEV), plug-in hybrid-electric (PHEV) and battery-electric vehicles (BEV). We use a discrete-choice approach to model the decisions that carsharing members make when selecting a vehicle for rental using survey data collected from members of Zipcar, the largest U.S. carsharing organization. We find that while service attribute (price, access distance and schedule) are the most important to the average carsharing user, there is significant heterogeneity around preferences for both vehicle types and service attributes.

The paper is organized as follows: In section 2, we describe our approach involving discrete choice analysis of survey responses. We describe the characteristics of the sample population in section 3, and present the results of the discrete choice analysis in section 4. Finally, we close in section 5 with discussion of the implications of our research, limitations and future research opportunities.

2 Approach

Our data was collected through an online survey of members of the largest carsharing operator in North America, conducted in October 2013. The carsharing operator has previously administered an annual survey asking members to describe their preferences (Zipcar 2012). The results of that survey (unpublished) indicated that the top three factors influencing users' vehicle reservation decisions were user proximity to the location of vehicles, the availability of vehicles at the user's desired time, and the price of vehicle rental. Interestingly, while environmental impact did not rank highly as a motivation for selecting a particular vehicle, nearly two thirds of respondents indicated that they were either 'interested' or 'extremely interested' in electric vehicles. We use these anecdotes to develop a stated-preference approach in which the effect of service attributes and vehicle technology are both explored. A key difference between prior studies of the decision to purchase a vehicle and the decision to reserve a carsharing vehicle is that carsharing provides the opportunity for users to trial a new technology without the investment risk.

In 2013, the carsharing provider sent an email to 68,982 randomly selected users, invitation them to participate in our survey with the incentive of a chance to win $50 in free driving credit for their completed response. 4,673 unique respondents (6.8%) began the survey, 4,133 (6.0%) completed most demographic information and 3,958 (5.7%) completed at least a portion of the discrete choice experiment. The survey consisted of three sections. The first section asked the respondent to provide basic demographic information, estimates of their typical reservation behavior (how frequently, how long, and how far they drive), and information about their public transit usage. Respondents were also asked questions about their experience with hybrid, plug-in hybrid and electric vehicles, to introduce the respondent to these terms and gather information about respondent exposure to these technologies. For example:

Some Zipcars are Hybrids (e.g. Toyota Prius). Hybrids run on gasoline, but use batteries and an electric motor to reduce the amount of gasoline the car uses. Have you ever driven a hybrid?

- *Yes, I own (or previously owned) a hybrid*

- *Yes, I've driven a Zipcar hybrid*

- *Yes, I've driven a hybrid elsewhere*

- *No, I haven't driven a hybrid*

- *I'm not sure*

In the second section of the survey, each respondent was presented with a discrete choice experiment in which they were asked to select the vehicle they would reserve for their typical carsharing trip. Each respondent was asked to complete four choice panels, comprising four available vehicle choices and a "none of the above" alternative. The choices offered in each panel varied along four attributes: the distance of the vehicle from the respondent (hereby referred to as "Access Distance"), the hourly rental price, the time the vehicle is available relative to the respondents preferred reservation time, and the vehicle fuel type. Rather than presenting vehicle type as specific vehicle model, which typically conflates numerous product attributes, the attribute was presented to users as "fuel type" with the options of Hybrid, Plug-In Hybrid (30 mile electric range plus gasoline), and Electric Vehicle (100 mile range).

Unlike some one-way carsharing, round trip carsharing users can typically book well in advance of their trip. If no desired vehicles are available at their preferred reservation time, users can see when vehicles are booked and adjust their schedules to a time when a closer or cheaper vehicle is available. A user adjusting his or her schedule could theoretically happen in thousands of different combinations of truncating or moving a reservation. We presented users with a simplified version of schedule adjustments: either a vehicle was available "Exactly when I want it" or as a difference from their preferred time of 30 minutes, 1 hour or 2 hours earlier or later. An example panel is shown in Figure 1:

Please indicate which of the following vehicles you would prefer for your typical reservation. Please assume that the vehicles are identical except for the characteristics listed.

Distance from you	0.1 miles	0.7 miles	0.1 miles	0.1 miles	None of these. I would reschedule the trip or travel a different way.
Price	$7.00/hour	$8.50/hour	$11.50/hour	$7.00/hour	
Schedule (difference from preferred time)	30 minutes earlier	2 hours later	2 hours later	30 minutes earlier	
Fuel type	Hybrid (gasoline)	Gasoline	Electric Vehicle (100 mile range)	Gasoline	
	●	●	●	●	●

Figure 1: Sample discrete choice panel presented to respondents.

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The levels used for each attribute in the discrete choice experiment are shown in Table 2, again selected to be representative of the actual levels commonly offered to carsharing users.

Table 1: Attributes and levels for vehicle choice experiment.

Variable	Units	No. of Levels	Levels
Hourly Price	US$/hour	6	$7/hour - $14.50/hour in $1.50 increments
Access Distance	miles	7	0.1 miles – 1.9 miles in 0.3 mile increments
Schedule	hours	7	Exactly when I need it
			30 minutes earlier or later
			1 hour earlier or later
			2 hours earlier or later
Vehicle Type		4	Gasoline
			Hybrid
			Plug-in Hybrid (30 mile electric range)
			Electric Vehicle (100 mile range)

The fractional factorial experimental consisted of fifty individual choice surveys, totaling 200 distinct choice panels. To avoid the potential loss of data due to the presentation of dominated alternatives, a random experimental design was rejected. The final design was a fractional factorial design in which utility of price, access distance and deviation from preferred schedule were assumed to be negative to generate a more efficient design. Given that no existing research provides an *a-priori* hypothesis about directionality of the utility of fuel type to carsharing, a utility seed was not used for fuel type. However, the experiment did sample the "gasoline" vehicle type more frequently so that conventional gasoline vehicles would make up approximately 50% of vehicle choices offered, reducing the potential for over-representation of alternative fuel vehicles.

In the third section of the survey respondents were asked to provide their opinions regarding specific vehicle models, including in situations where large passenger and/or cargo capacity are required. A complete list of survey questions is included in Appendix A.

3   Respondent Characteristics

The demographics of our sample are reported in Table 2. Our respondents were generally young (largest cohort 26-30 years old) and without children, with slighter more male respondents than female. Approximately two-thirds of respondents lived in households that did not own a vehicle, and the majority of households that did own a vehicle had only one vehicle. Most respondents lived in large metropolitan areas where this carsharing operator is active, including: Boston, Chicago, New York, San Francisco, Toronto and Washington, D.C.

For 39% of respondents (N=1605), we were able to obtain information about median trip length and travel distance in the prior calendar year. The demographics of this subset group are also shown in Table 2, and are similar to the demographics of the entire group. For this group of users we were able to compare their reported typical travel distance with their actual median travel distance (in miles) and trip duration (in hours) from the prior calendar year. These comparisons are shown in Figure 2 and Figure 3.

Table 2: Demographic information for all respondents and for those for whom actual usage information was available.

Characteristic	Level	% Respondents (N=4133)	% Actual Usage Subset (N=1605)
Gender	Male	52%	50%
	Female	47%	49%
	Not Given	1%	1%
Age	18-21	9%	5%
	22-25	18%	14%
	26-30	23%	23%
	31-35	17%	18%
	36-45	16%	19%
	46-55	9%	10%
	56+	8%	10%
Children in Household	0	86%	85%
	1	8%	9%
	2	4%	4%
	3	1%	1%
	4+	1%	1%
Cars Owned in Household	0	70%	75%
	1	20%	18%
	2	7%	5%
	3	2%	1%
	4+	1%	0%
Transit Modes Used Regularly	Bicycle	34%	35%
	Bus	63%	65%
	Subway	61%	67%
	Train	31%	32%
	Walk	80%	83%

Respondents were able to effectively recall the duration of their typical reservation duration, with no statistically significant difference between the reported average and actual average trip duration observed at $p=0.1$ (paired T-test). However, respondents performed relatively less well when estimating the distance they travel in a typical reservation (Figure 3). Our data indicates that respondents overestimate the distance they travel, with a mean of the differences of 2.7 miles. The mean reported travel distance was 48.3 miles while a mean of all users' median travel distance of 45.7 miles. This overestimation is statistically significant at $p=0.05$ (paired T-test). The overestimation of travel distance is potentially problematic for the deployment of alternative fuel vehicles with a limited range, such as battery electric vehicles

(BEVs), into shared vehicle fleets. Carsharing users may avoid reserving alternative fuel vehicles in the flawed belief that the vehicle is not capable of meeting the driving requirements of a specific trip.
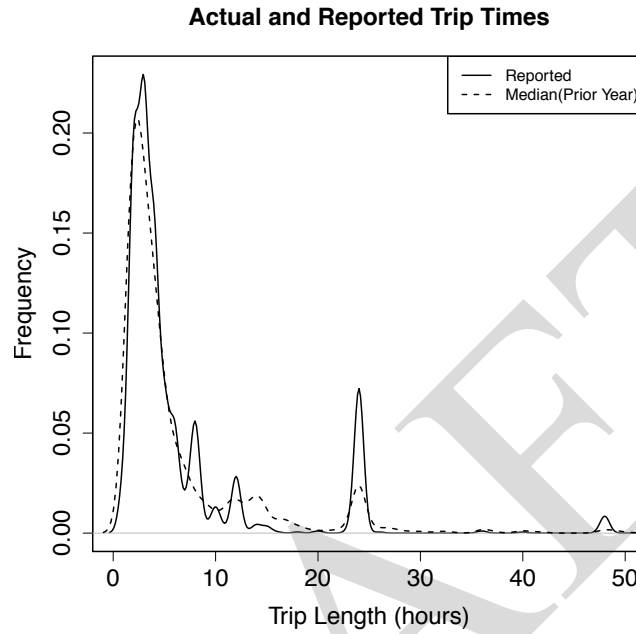
Actual and Reported Trip Times

Figure 2: User recollection of trip duration (in hours) vs. median duration in prior calendar year.
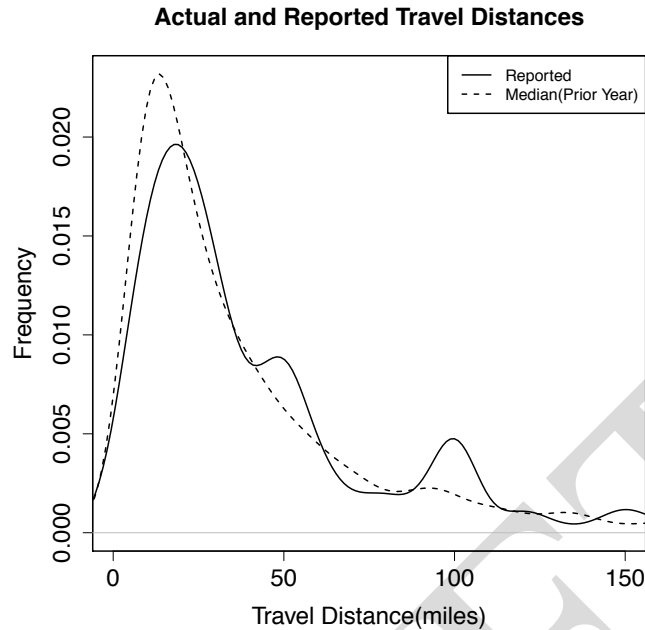
Actual and Reported Travel Distances

Figure 3: User recollection of travel distance (in miles) vs. median length in prior calendar year.

The responses in our sample indicate that carsharing is an important source of exposure to alternative fuel vehicles, hybrid vehicles in particular (Table 3). More than half of respondents (50.5%) have driven a Hybrid vehicle through this carsharing service – far more than those who own or have owned a hybrid (3.3%) and those who have driven a hybrid elsewhere (13.8%). In contrast, more than 90% of respondents reported having never driven a PHEV or a BEV or not knowing if they had, consistent with the very low penetration of PHEVs and BEVs in both the carsharing operator's fleet and in the U.S. light duty vehicle fleet.

Table 3: Experience with Alternative Powertrain Vehicles

Experience	Hybrid	PHEV	EV
Own / Owned	3.3%	0.1%	0.1%
Driven through Zipcar	50.5%	3.3%	2.3%
Driven Elsewhere	13.8%	2.9%	3.9%
Never Driven	28.3%	86.3%	86.4%
Don't Know	4.1%	7.5%	5.3%

As of October 2013, the carsharing provider reported membership of approximately 709,000 in the U.S. and Canada. While the size and composition of the fleet varies over time, a sample taken in the year preceding the launch of this survey suggested that approximately 892 vehicles, or approximately 10% of the fleet at the time, were hybrids. If our respondent sample is representative of the total membership of this carsharing operator and vehicle distribution is consistent, our results imply that approximately 358,000 members have been exposed to Hybrid

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vehicles through their participation in carsharing, or approximately 400 users exposed per Hybrid vehicle in active service. The large number of users driving hybrid vehicles in our sample may be explained by the hybrid vehicle pricing model employed by this carsharing operator: hybrid vehicles are typically priced more cheaply than most other vehicles, so users looking for the cheapest vehicles will frequently drive hybrids.

4 Discrete Choice Analysis

We analyze data from the discrete choice experiment to quantify how carsharing users trade off carsharing service attributes in carsharing reservation decision-making. First, we estimate a model incorporating the key carsharing service and vehicle attributes, in both multinomial logit (MNL) and mixed logit (ML) forms, to quantify the preferences of users for these attributes and random taste variation. We then estimate a larger multinomial logit model adding the interaction of these service and vehicle preferences with user demographics, to understand how preferences may change over subsets of respondents. Models were estimated using maximum likelihood estimation with the Biogeme software package (Bierlaire, 2003).

The probability of person n choosing alternative i is standard logit:

$$P_{ni} = \frac{e^{v_{ni}}}{\sum_j e^{v_{nj}}}$$

where v_{ni} is the observable portion of the utility of choice i. The utility of each shared vehicle available for reservation is specified as observed component v_{nj} and unobserved component ε_{nj}:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta'_n x_{nj} + C'_n y_{nj} + \varepsilon_{nj}$$

Where x_{nj} are observed variables of the carsharing service (e.g. Access Distance, Price and Schedule), y_{nj} are observable variables of the vehicle alternatives (e.g. Powertrain type) and decision maker, and β' and C' are estimated coefficients. ε_{nj} is a random term that is i.i.d. extreme value. In the mixed logit model, some coefficients are modeled as random variables for which we estimate the mean and standard deviation. We include Price and Access Distance as continuous variables. Schedule is included as a series of dummy variables with "Exactly when I want it" normalized to zero. Vehicle type is also included as a dummy variable with gasoline vehicles normalized to zero utility. Unlabeled alternatives are not inherently different except for specified attributes, so no alternative specific constant is used.

The results of the multinomial logit and mixed logit models are shown in Table 4.

<p style="text-align:center">**Table 4: Results for Multinomial Logit and Mixed Logit models.**</p>

Name	Multinomial Logit Model			Mixed Logit Model		
	Coefficient	Std Error	t-test	Coefficient	Std Error	t-test
Price ($/hour)	-0.349	0.00625	-55.79	-0.587	0.015	-39.19
σ (Price)	-	-	-	0.42	0.0149	-28.23
Access Distance (miles)	-0.734	0.0205	-35.75	-1.18	0.0451	-26.17
σ (Access Distance)	-	-	-	1.55	0.0588	26.4
Schedule 30 min early	-0.753	0.0323	-23.3	-0.989	0.0416	-23.74
Schedule 30 min late	-0.624	0.0386	-16.16	-0.867	0.0501	-17.29
Schedule 1 hour early	-0.872	0.0415	-20.99	-1.14	0.053	-21.53
Schedule 1 hour late	-0.581	0.0396	-14.69	-1.05	0.0566	-18.61
Schedule 2 hours early	-0.963	0.0424	-22.72	-1.57	0.0607	-25.8
Schedule 2 hours late	-1.81	0.0523	-34.66	-2.68	0.0831	-32.27
Hybrid	0.141	0.0289	4.88	0.125	0.0413	3.03
σ (Hybrid)	-	-	-	0.634	0.105	6.02
Plug-In Hybrid	-0.172	0.0284	-6.06	-0.341	0.0471	-7.23
σ (Plug-In Hybrid)	-	-	-	1.02	0.0831	12.23
Electric Vehicle	-0.159	0.0295	-5.4	-0.414	0.052	-7.96
σ (Electric Vehicle)	-	-	-	1.22	0.0823	14.85
Sample Size:	13002			13002		
Init. log-likelihood:	-18024.599			-15689.874		
Final log-likelihood:	-14854.11			-13907.453		
Likelihood Ratio Test:	6340.979			3564.841		
Rho bar for the initial model:	0.175			0.113		

As expected, Price and Access Distance are found to have negative coefficient: the utility of a shared vehicle decreases as its price or distance from the user increases. Similarly, a vehicle that is not available exactly when the user wants it reduces utility. Coefficients on schedule deviations less than one hour are relatively uniform, but deviations of two hours earlier or later are more strongly negative.

The coefficient for hybrid vehicles is positive relative to gasoline vehicles, while coefficients for PHEVs and BEVs are negative relative to gasoline, suggesting that all else equal, carsharing users prefer driving a hybrid vehicle, but not plug-in electric vehicles. Possible explanations for this result is that carsharing users are unfamiliar with these new and advanced technologies, or they understand the technology but dislike different attributes of these vehicles, such as the need to plug-in the vehicle at the end of each trip. All parameters are highly significant.

Model coefficients, expressed in terms of utility, can be divided by one another to calculate willingness to pay. Willingness to pay values allow us to understand exactly how much of an improvement in one attribute is needed to compensate for a loss in another attribute. By taking the ratio of coefficient on price divided by distance in the MNL model, we find that respondents value one additional mile of access distance to a vehicle approximately the same as a $2.10/hour increase in price. Schedule deviations of up to one hour were valued the same as an increase of $1.66 - $2.50/hour in vehicle price. Willingness to pay values for vehicle type in the MNL model are +$.40/hour for hybrid vehicles, but -$0.46/hour for BEVs and -$0.49/hour for PHEVs.

In the Mixed Logit model the relative scale of coefficient means is similar. Significant heterogeneity is observed around all variables, with the highest standard deviation around Access Distance and both Plug-In vehicle types. By definition, this variation is considered random taste variation in the Mixed Logit specification.

To uncover systematic variation in demographic groups, we specify a further Multinomial Logit model (Table 5, Table 6, Table 7, and Table 8) in which we introduce interactions between service attributes and user demographics to explore heterogeneity in preferences among respondents. We interacted gender with price, a vector of demographic dummy variables with an intercept interacted with access distance, reported advanced planning with schedule deviation, and a piecewise linear variable for travel distance with vehicle powertrain type. In all cases, interactions with Access Distance are added to the base Access Distance coefficient. Hence positive values of Access Distance interactions result in a less negative coefficient on Access Distance, or increased willingness to use a carsharing vehicle located farther away. While numerous model specifications were tested, these interactions provided the best overall model fit.

Table 5: User characteristics used in models and definitions.

User Characteristics	Type	Definition
Travel Distance	Numeric	User reported typical trip length (miles)
Has_Children	Dummy	User reported at least one child under 18 in the household
Train_User Bus_User Subway_User	Dummy	User reports regularly using train, bus or subway train as a travel mode.
Metro: City (e.g. City: Metro_Boston)	Dummy	City where user primarily uses the carsharing service.
Plan: [time] (e.g. Plan: Under 1 hour)	Dummy	User reported time in advance they typically reserve a carsharing vehicle.

Coefficients on dummy variables for Boston, Chicago, Miami and Washington D.C. are significantly negative, indicating that these respondents place more value on a vehicle close to them than the base group (New York). Some of these differences (e.g. Miami or Chicago) may be explained by climate. However, the explanation for others (e.g. Washington, D.C.) is less clear, and are perhaps the result of unobserved variables such as income or transit density not captured by transit dummy variables. Results for interactions of Access Distance with transit use are significant and positive for users who report regularly using Bus or Train. These results suggest that Bus and Train users experience less disutility for a vehicle located farther away. Surprisingly, interactions of Access Distance with a dummy variable for Household Children >1 also produces a positive result. This outcome may highlight an income effect unobserved in this data set.

Table 6: Results for Interaction Model--Price and Access Distance interactions.

Attribute	Coefficient	Std Error	t-test
Price & Male	-0.327	0.00741	-44.11
Price & Female	-0.374	0.00795	-46.99
Access Distance	-0.686	0.058	-11.81
Access Distance & Has Children	0.174	0.0718	2.42
Access Distance & Train_User	0.081	0.0383	2.12
Access Distance & Bus_User	0.0716	0.037	1.93
Access Distance & Subway_User	-0.0472	0.0465	-1.02
Access Distance & Metro:Atlanta	-0.162	0.167	-0.97
Access Distance & Metro:Austin	0.0538	0.221	0.24
Access Distance & Metro:Baltimore	0.00871	0.136	0.06
Access Distance & Metro:Boston	-0.186	0.06	-3.1
Access Distance & Metro:Chicago	-0.345	0.0729	-4.74
Access Distance & Metro:Denver	0.232	0.31	0.75
Access Distance & Metro:LosAngeles	0.0752	0.116	0.65
Access Distance & Metro:Miami	-1.04	0.451	-2.3
Access Distance & Metro:Milwaukee	-0.414	0.321	-1.29
Access Distance & Metro:Minneapolis	-0.298	0.298	-1
Access Distance & Metro:Philadelphia	-0.0733	0.105	-0.7
Access Distance & Metro:Pittsburgh	0.0268	0.162	0.17
Access Distance & Metro:Portland	-0.233	0.117	-1.99
Access Distance & Metro:Providence	-0.0686	0.177	-0.39
Access Distance & Metro:San Diego	-0.1	0.334	-0.3
Access Distance & Metro:SanFrancisco	-0.0669	0.0677	-0.99
Access Distance & Metro:Seattle	-0.249	0.104	-2.39
Access Distance & Metro:Toronto	0.0435	0.0712	0.61

Access Distance & Metro:Universities	0.003	0.0742	0.04
Access Distance & Metro:Vancouver	0.21	0.119	1.76
Access Distance & Metro:WashingtonDC	-0.336	0.0709	-4.74
Sample size:	13002		
Init log-likelihood:	-18024.599		
Final log-likelihood:	-14735.635		
Likelihood ratio test for the init. model:	6577.929		
Rho bar for the init. model:	0.178		

Table 7: Results for Interaction Model--Schedule and Planning interactions.

Attribute	Coefficient	Std Error	t-test
Schedule: 2hrs Early & Plan: Under 1 hr	-0.852	0.122	-6.96
Schedule: 2hrs Early & Plan: Hours	-0.882	0.0725	-12.17
Schedule: 2hrs Early & Plan: day	-1.11	0.0631	-17.66
Schedule: 2hrs Early & Plan: week	-0.778	0.119	-6.51
Schedule: 2hrs Early & Plan: month	-0.635	0.412	-1.54
Schedule: 1hr Early & Plan: under1hr	-0.89	0.133	-6.69
Schedule: 1hr Early & Plan: hours	-0.875	0.0733	-11.94
Schedule: 1hr Early & Plan: day	-0.992	0.0624	-15.89
Schedule: 1hr Early & Plan: week	-0.53	0.115	-4.61
Schedule: 1hr Early & Plan: month	0.0112	0.409	0.03
Schedule: 30min Early & Plan: Under 1hr	-0.675	0.1	-6.73
Schedule: 30min Early & Plan: hours	-0.766	0.0573	-13.38
Schedule: 30min Early & Plan: day	-0.777	0.0473	-16.43
Schedule: 30min Early & Plan: week	-0.791	0.101	-7.85
Schedule: 30min Early & Plan: month	-0.725	0.374	-1.94
Schedule: 30min Late & Plan: under1hr	-0.435	0.113	-3.87
Schedule: 30min Late & Plan: hours	-0.619	0.0684	-9.04
Schedule: 30min Late & Plan: day	-0.695	0.057	-12.2
Schedule: 30min Late & Plan: week	-0.581	0.115	-5.03
Schedule: 30min Late & Plan: month	-0.487	0.433	-1.13
Schedule: 1hr Late & Plan: under1hr	-0.422	0.118	-3.57
Schedule: 1hr Late & Plan: hours	-0.577	0.0679	-8.49
Schedule: 1hr Late & Plan: day	-0.621	0.0569	-10.92
Schedule: 1hr Late & Plan: week	-0.604	0.12	-5.05
Schedule: 1hr Late & Plan: month	-0.168	0.415	-0.41
Schedule: 2hrs Late & Plan: under1hr	-1.33	0.119	-11.21
Schedule: 2hrs Late & Plan: hours	-1.72	0.0754	-22.84
Schedule: 2hrs Late & Plan: day	-1.9	0.0663	-28.69
Schedule: 2hrs Late & Plan: week	-2.01	0.116	-17.43
Schedule: 2hrs Late & Plan: month	-1.6	0.518	-3.1

Table 8: Results for Interaction Model--Vehicle Powertrain type and Travel Distance interactions.

Attribute	Coefficient	Std Error	t-test
Hybrid	0.129	0.118	1.1
PHEV	-0.054	0.113	-0.48
EV	0.0878	0.115	0.76
EV & Travel Distance <20	-0.00165	0.00746	-0.22
Hybrid & Travel Distance <20	0.00678	0.00757	0.9
PHEV & Travel Distance <20	0.00458	0.00723	0.63
EV & Travel Distance 20-40	-0.0104	0.00607	-1.71
Hybrid & Travel Distance 20-40	-0.00196	0.006	-0.33
PHEV & Travel Distance 20-40	-0.0134	0.00581	-2.31
EV & Travel Distance 40-60	-0.00632	0.00845	-0.75
Hybrid & Travel Distance 40-60	-0.0127	0.00842	-1.5
PHEV & Travel Distance 40-60	-0.00798	0.00815	-0.98
EV & Travel Distance 60-80	-0.00138	0.0104	-0.13
HEV & Travel Distance 60-80	0.0107	0.0101	1.07
PHEV & Travel Distance 60-80	-0.00145	0.00999	-0.14
EV & Travel Distance 80-100	-0.0158	0.0101	-1.56
HEV & Travel Distance 80-100	-0.0155	0.00948	-1.64
PHEV & Travel Distance 80-100	0.00312	0.00955	0.33
EV & Travel Distance 100-120	-0.01	0.00957	-1.05
HEV & Travel Distance 100-120	0.00745	0.0083	0.9
PHEV & Travel Distance 100-120	-0.00939	0.00837	-1.12
EV & Travel Distance >120	-0.00153	0.00153	-1
HEV & Travel Distance >120	-0.00165	0.00132	-1.25
PHEV & Travel Distance >120	-0.000132	0.00123	-0.11

The interaction of schedule and advanced planning (Figure 4) produces a number of interesting results. Respondent distaste for a two-hour delay is universal across planning groups. However, users that plan either far in advance (more than a month) or very late (less than an hour in advance) show generally more tolerance for schedule deviations. The significance of coefficients for those who plan more than a month in advance are relatively weak due to a low number of observations for such users. For users who book less than an hour before their trip, we see an asymmetry, with schedule shifts earlier generating higher levels of disutility than schedule delays, as these would likely result in a truncated trip duration, not just a schedule shift.

	Vehicle Availability						
	2 hours early	1 hour early	30 min early	Exactly when I prefer	30 min late	1 hour late	2 hours late
…less than an hour in advance	-0.85	-0.89	-0.68	0	-0.44	-0.42	-1.33
…several hours in advance	-0.88	-0.88	-0.77	0	-0.62	-0.58	-1.72
…more than a day in advance	-1.11	-0.99	-0.78	0	-0.70	-0.62	-1.90
…more than a week in advance	-0.78	-0.53	-0.79	0	-0.58	-0.60	-2.01
…more than a month in advance	-0.64	0.01	-0.73	0	-0.49	-0.17	-1.60

(Row label spanning vertically: Typically Reserve…)

Figure 4: Interactions of Schedule and Advance Planning.

The utility of each vehicle type varies strongly with the length of a trip (Figure 5). The utility of hybrid vehicles is greater than or similar to the utility of gasoline vehicles across a wide range of reservation distances. However, the utility of plug-in electric vehicles is never strongly positive and declines noticeably with increasingly reservation distance, affecting EVs more than PHEVs. This suggests that carsharing users become increasingly sensitive to the vehicle technology as the length of their reservation increases, consistent with concerns about recharging and range anxiety for plug-in electric vehicles.
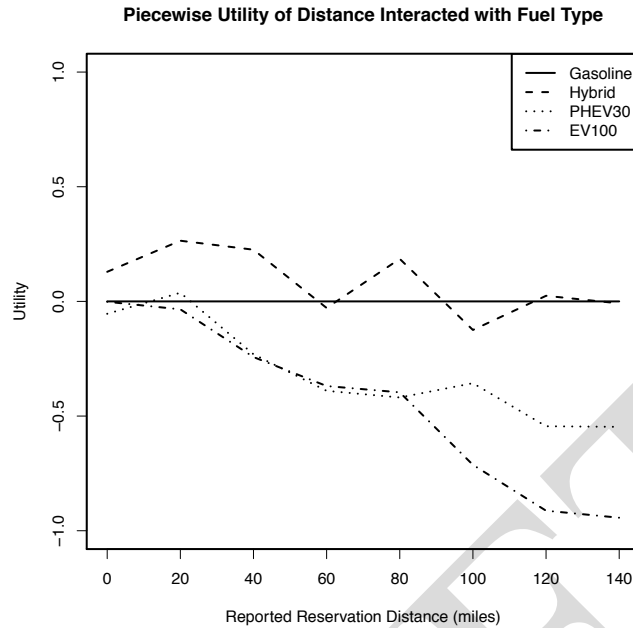
Piecewise Utility of Distance Interacted with Fuel Type

Figure 5: Utility of vehicle type interacted with travel distance.

5   Discussion

We develop new insights about the decision-making in carsharing analyzing decision-making from the perspective of the individual user. Using a stated preference discrete choice experiment, we quantify how carsharing users trade-off service attributes, deriving the most utility (not surprisingly) from a vehicle available when and where they want it, at the lowest price possible. We find schedule to be an important decision variable, with users willing to shift their travel slightly to select a slightly closer or cheaper vehicle, and in rough numbers, $2/hour in price is approximately equivalent to a mile of Access Distance or shifting travel schedule by up to an hour. While most users appear to have reservations about plug-in electric vehicles (both BEVs and PHEVs), many respondents prefer hybrids to conventional gasoline vehicles. We find widespread exposure to hybrid vehicle technology through carsharing. The ratio of users exposed to vehicles in service is nearly 400:1, many times higher than the 1-2 drivers that typically drive a vehicle owned by a single household.

Quantifying user attitudes to plug-in electric vehicles in carsharing is particularly timely given sustained efforts by policymakers to introduce electric vehicles to U.S. roads and the subsequence appearance of these vehicles into carsharing fleets. User aversion to fully electric vehicles for trips exceeding their range is understandable, as users may wish to avoid disrupting their travel to recharge. However, the similar disutility of plug-in hybrid vehicles seems less

rational, since these vehicles simply operate as hybrids after the battery is exhausted. These preferences may indicate that users do not fully understand the capabilities of PHEVs and assume that vehicle capability will be diminished after the battery is exhausted, noting that few respondents have first-hand experience with these technologies—either through the carsharing operator or elsewhere. Alternatively, users may have reservations about the plug-in procedure itself and avoid vehicles that need to be unplugged at the beginning of a reservation and plugged-in at the end. Education of members and incentives to use plug-in vehicles may be influential in stimulating greater use of plug-in vehicles within carsharing. From a policy perspective, the high ratio of users exposed to hybrid vehicles in carsharing supports the case for Zero Emission Vehicle policies that provide incentive credits for shared use of some PHEVs and EVs: carsharing may a de facto test drive for some users, offering them the chance to drive a range of vehicles without ever visiting a dealer. However, numerous questions remain, principally: under what conditions does exposure to new vehicle technologies in the carsharing context lead to increased adoption of advanced technology vehicles across the light duty fleet.

More broadly, shared mobility services present an interesting laboratory for the study of decision-making, because users make regular and explicit decisions revealing their beliefs and preferences. The overestimates of travel distance by respondents may be a manifestation of risk-aversion, in which users seek (explicitly or subconsciously) to avoid the anxiety of running out of time at the end of a shared vehicle reservation. Alternatively, carsharing users who often drive less frequently may be less proficient at predicting their travel patterns. The result may be that carsharing users avoid reserving limited-range electric vehicles even if those vehicles have sufficient range for the user's trip, lead to underutilization of electric vehicles. With greater deployment of such range-limited vehicles, new tools may be needed to assist drivers in finding a suitable vehicle for their travel. More accurate distance-to-empty, energy consumption and recharging time estimates (Rodgers et al, 2013) would be particularly valuable in the carsharing context.

Numerous opportunities for future work exist. Other vehicle attributes including brand and body style are likely to be a factor in the rental decision of some users. For instance, users may seek vehicles with large seating or cargo capacity to accomplish specific tasks such as moving furniture. Such tradeoffs are particularly important in round-trip carsharing, where users typically have a large selection of vehicles to choose from. Earlier we noted the potential importance of carsharing as a mechanism for trialing new technologies. However, not enough is known about the carsharing membership lifecycle at present to speculate about the extent of this influence. While most respondents to our survey do not own a car currently, many will buy one

in the future, and an important issue for the future of carsharing is understanding the duration of carsharing membership and the vehicle purchasing behavior of former carsharing users. Finally, the potential for hypothetical bias in responses is always present with stated preference studies, to an unknown extent. Further insight could be gained from extending our analysis using revealed preference data, if actual reservation data can be obtained from a carsharing organization that included both the reservation decisions made by users and the choice set of vehicles that was offered to the user.

6   Acknowledgements

7   References

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8 Appendix A: Survey Questions

1. What is your age?
   •18-21 •22-25 •26-30 •31-35 •36-45 •46-55 •56+

2. What is your gender identity?
   •Male   •Female   •Prefer not to answer

3. In what region do you primarily use Zipcar services? If you are not based in one of our larger markets, please choose the "Universities" option.

4. How many people live in your household, including you?
   •1 •2 •3 •4 •5+

5. How many children under the age of 18 live in your household?
   •0 •1 •2 •3 •4+

6. Besides Zipcar, what other modes of transportation do you use regularly?
   •Bicycle •Bus •Subway •Train •Walk •Other

7. How many personal cars are owned or leased by your household?
   •None, Zipcar all the way! •One •Two •Three •Four or more

8. Please list the make and models of the cars owned and leased in your household. (i.e. 2010 Toyota Camry Hybrid)

9. Please select the primary reason your household has one or more cars.
   - We don't make car payments and don't have to pay for parking, so the costs aren't that high
   - We just like having a personal car or truck
   - We use Zipcar when we want a nicer car than our personal cars or trucks
   - One or more family member has to commute to work or school regularly
   - We use Zipcar only for special cars for a specific task, like if we need a van or pickup
   - There aren't enough Zipcars in my area that I can rely on the service
   - We have one or more kids and it's more convenient
   - Other

10. How often do you rent a Zipcar?
    - More than once a week
    - Once a week
    - 2-3 times per month
    - Once a month
    - Less than once a month

11. Some Zipcars are Hybrids (e.g. Toyota Prius). Hybrids run on gasoline, but use batteries and an electric motor to reduce the amount of gasoline the car uses. Have you ever driven a hybrid?
    - Yes, I own (or previously owned) a hybrid
    - Yes, I've driven a Zipcar hybrid
    - Yes, I've driven a hybrid elsewhere
    - No, I haven't driven a hybrid
    - I'm not sure

12. Some Zipcars are <u>Plug-In hybrids</u> (e.g. Chevrolet Volt). Plug-In hybrids are like regular hybrids, but can be also recharged directly with electricity, to travel farther under electric power and further reduce the gasoline the cars use. Have you ever driven a Plug-In hybrid?
    • Yes, I own (or previously owned) a plug-in hybrid
    • Yes, I've driven a Zipcar plug-in hybrid
    • Yes, I've driven a plug-in hybrid elsewhere
    • No, I haven't driven a plug-in hybrid
    • I'm not sure
13. Some Zipcars are <u>Electric cars</u> (e.g. Nissan Leaf). Electric cars use no gasoline, being recharged 100% using electricity. Have you ever driven an electric car?
    • Yes, I own (or previously owned) an electric car
    • Yes, I've driven a Zipcar electric car
    • Yes, I've driven an electric car elsewhere
    • No, I haven't driven an electric car
    • I'm not sure
14. How far ahead do you typically make your reservation for a Zipcar?
    • More than a month before my trip
    • More than a week before my trip
    • More than a day before my trip
    • Several hours before my trip
    • Up to an hour before my trip
15. Which of the following best describes your preferences when selecting a Zipcar?
    • I always take the same brand and model Zipcar if possible
    • I prefer the same brand and model Zipcar
    • No Preference
    • I prefer to try different brands and models of cars
    • I always try to take something new
16. Please rate your agreement with the following statement: "I like Zipcars that have logos and other Zipcar branding on the car."
    • Strongly agree
    • Agree
    • Neither agree nor disagree
    • Disagree
    • Strongly disagree
17. In a typical reservation, how many <u>hours</u> do you keep your Zipcar?

18. In a typical Zipcar reservation, how many <u>miles</u> do you drive your Zipcar?

19. "In the following 4 questions, we ask you to select which vehicle you would reserve for your typical Zipcar trip given a range of vehicle options.

    Please select the vehicle that best suits your needs.
    Assume that all gasoline cars are filled and electric cars are fully charged when you take them, and that the vehicles are otherwise identical except for the differences shown."

    [Conjoint Analysis (Discrete Choice)]

20. Zipsters sometimes need vehicles with large passenger and cargo capacity (such as SUVs, Zipvans, and pickup trucks) for certain trips. How often do you take trips that require larger vehicles?
- Always
- Often
- Sometimes
- Rarely
- Never

21. Which of the following apply to you? (Check all that apply)

- I always prefer a larger vehicle
- I take a larger vehicle when many people are traveling with me
- I take a larger vehicle when I need to carry bulky cargo
- I take a larger vehicle only when nothing else is available
- Other

22. In a trip which requires a larger vehicle, which of the following would you prefer?
- Minivan (e.g. Mazda5 or Toyota Sienna)
- Pickup Truck (e.g. Toyota Tacoma)
- Compact SUV (e.g. Honda CRV)
- Zipvan (Cargo Van e.g. Ford Econoline)

23. Please rate your level of satisfaction with the following brands and models of Zipcars.

Please only rate the vehicles which you have used through Zipcar.

- Audi A3
- BMW 3 Series
- Chevrolet Volt
- FIAT 500
- Ford E-150 (Zipvan)
- Ford Escape
- Ford Focus
- Honda Civic
- Honda CR-V
- Honda Fit EV
- Honda Insight Hybrid
- Hyundai Veloster
- Mazda 3
- Mercedes C250/C300
- MINI Cooper
- Nissan Frontier
- Nissan Sentra
- Toyota Prius Hybrid
- Toyota Sienna
- Toyota Tacoma
- Volkswagen Golf

24. What kinds of cars would you like to see more of in our fleet, and why?

25. Please let us know if you have any other comments or suggestions about our service.