Steering Short-term Demand for Car-sharing: A Mode Choice and Policy Impact Analysis by Trip Distance

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ABSTRACT
Car-sharing could have substantial benefits. However, there is not enough evidence about if more people choosing car-sharing would reduce private car usage or public transport demand. This work aims to bring forward some insights by studying short-term car-sharing choice behavior. A mode choice analysis is conducted first followed by a simulation analysis to evaluate modal substitution pattern. Policy implications are obtained in terms of the possible measures that could effectively bring down private car usage. The case study is Taiyuan-China; stated and revealed preference data are collected. Mixed nested logit models are developed to study the pooled SP/RP data. The analysis is conducted separately for a shorter trip case (2km to 5km) and a longer trip case (more than 5km) to examine if results would differ by distance. It is found that raising the cost of private car usage (travel cost, parking cost) should be prioritized for shorter trips since car is more difficult to be substituted when trip distance increases. Shorter trips also need such direct measures to help suppress the demand for private car when promoting a car-sharing service; otherwise car-sharing would attract more bus users instead. Longer trips need a more effective solution to bring down private car usage and that is discovered as making car-sharing service more appealing so that it can serve as a practical substitute to private car. A number of informative indicators (e.g. willingness to pay for travel time savings, direct and cross point elasticity) are also derived to enrich the findings.

Keywords: Car-sharing policy, Mode choice, Value of time, Mixed NL model, Pooled SP/RP data, China

1. INTRODUCTION

Over the last two decades car-sharing services have sprung up across the globe (Shaheen et al., 1999; Enoch and Taylor, 2006; Shaheen and Cohen, 2007; Shaheen et al., 2009; Shaheen and Cohen, 2013). From the traditional round-trip mode to the recent free-floating mode, users have enjoyed the increasing flexibility that car-sharing offers. The service may also bring wider social benefits. On the one hand, many car-sharing operators have replaced their gasoline fleets with the more environmental-friendly electric vehicles in the last few years (Bakker and Trip, 2013; Shaheen and Chan, 2015). On the other hand, various studies have shown that car-sharing could help to reduce car ownership and traffic volume (Cervero et al., 2007; Martin et al., 2010; Mishra et al., 2015; Bondorová and Archer, 2017; Vij, 2017). In addition, Clewlow (2016) indicated that the personal vehicles owned by frequent car-sharing users were more likely to be those with a smaller environmental footprint (e.g., hybrid, plug-in hybrid electric, and battery electric).

Given the expected benefits of car-sharing, many research attempts have been made with respect to the demand for using this service. Jorge and Correia (2013) conducted a literature review study summarizing the important works by the time. One of the gaps they identified was a lack of clear evidence on the modal substitution pattern, and in particular, if more people using car-sharing "reduces the use of private vehicles or if, on the contrary, it reduces the number of public transport users (p.216)". This is the information that policy makers are keen to find out, especially when they need to determine whether or not to endorse car-sharing (via subsidies, legislation etc.). Later, Le Vine et al. (2014) investigated how an introduction of car-sharing service could influence car and public transport usage. The work showed the answer to such a puzzle could be a joint outcome of travellers' long-term and short-term behaviors; in other words, tactical-level behaviors at the short-run (i.e. mode choice for a trip, such as car-sharing, car or public transport) could be influenced by strategic-level behaviors at the long-run (i.e. mobility resource choice, such as car ownership and subscription to a car-sharing program). Nevertheless, given the limited amount of car-sharing choice data collected, the contribution of this work is more on the joint analytical framework it developed, rather than providing empirical answers to the aforementioned puzzle. Kopp et al. (2015) also explored modal substitution pattern by comparing the travel behavior across a car-sharing member group and a non-member group. They found public transport demand was similar, while the demand for motorized private transport was significantly lower in the member group. However, they noticed that the result could be biased due to the sampled car-sharing user group already had a low rate of motorized private transport usage before joining the car-sharing scheme, and hence, further research was called for. One earlier attempt not mentioned by Jorge and Correia (2013), was made by Martin and Shaheen (2011), in which the authors looked directly at their survey statistics and saw car-sharing's impact on travel pattern was rather complex, where members from some organizations increased their public transits, while others shifted away, and the magnitudes were largely variable across member groups. In general, more robust evidence on modal substitution pattern is needed to better inform policy decisions. Unfortunately, to our best knowledge, the puzzle has remained overlooked apart from the few studies mentioned above, though some more recent works have shown up and significantly enhanced our understanding of car-sharing choice behavior. Their main contributions are highlighted below.

Carteni et al. (2016) used a binomial logit choice model to analyze the mode choice between car-sharing and private car. The key finding from the choice model and the follow-up elasticity analysis was that travel cost has a much greater impact than travel time on affecting car-sharing choice. Similarly, in De Luca and Di Pace (2015), travel cost was identified as one of the critical factors alongside access time to car-sharing spots, trip frequency, car availability and the type of trip etc. Moreover, De Luca and Di Pace (2015) showed via a cross-elasticity analysis that a change in car-sharing travel cost has much larger effect on the probability to choose to carpool than on the probabilities to choose bus and private car. Martinez et al. (2017) highlighted an important conclusion that the preference towards car-sharing would increase with trip length; in other words, the service could more likely be chosen as trips became longer. Becker et al. (2017) put particular attention on the socio-economic groups from which the usage of free-floating and station-based car-sharing services could come from. The results demonstrated both schemes could attract younger and educated people, which were in line with the key findings from the other two studies dedicated to revealing the influence of socio-economic factors on the general car-sharing choice (Dias et al., 2017; Prieto et al., 2017). However, a critical difference was emphasized such that a free-floating service was normally used by those higher incomes earners whose home location poorly served by public transportation whereas the station-based was preferred by self-employed workers who would appreciate the flexibility of using a car when needed. Apart from those rather fundamental factors and effects, a few more novel subjects were also explored, such as a parking price increase (Balac et al., 2017), introducing autonomous vehicle fleets (Winter et al., 2017), placing a station outside a technology firm (El Zarwi et al., 2017), all of which could potentially boost car-sharing adoption.

Some studies applied more advanced modeling techniques to investigate the impacts of latent variables/unobserved attributes on car-sharing choice. Kim et al. (2016) developed a hybrid choice model and found that social influence (i.e. the phenomenon that individuals' decisions are influenced by the choices made by others) was significant in car-sharing decisions. Specifically, the magnitude of social influence could vary according to the strength of social relationship between individuals. Efthymiou and Antoniou (2016) focused on latent classes in a case study at Athens, Greece. They demonstrated that people who used taxi for social activities, those with medium to low income, and the environmentally conscious, were more willing to join a hypothetical car-sharing scheme. Recently, Fleury et al. (2017) analyzed the results from an online survey of 259 people in France and highlighted that perceived effort expectancy (i.e. degree of ease associated with use) was the most important psychological factor that could determine the intention to use corporate car-sharing.

Many earlier works that involved factors affecting car-sharing choice and demand have been captured by Jorge and Correia (2013) and for which repeated reviews should be avoided, for example Catalano et al. (2008), Zheng et al. (2009), Morency et al. (2012), Ciari et al. (2013) and De Lorimier and El-Geneidy (2013), though two of them (Catalano et al., 2008; Zheng et al., 2009) also attempted to study modal substitution patterns; nevertheless, both works have rather specific focuses (i.e. Catalano et al. (2008) analyzed 500 commuters' morning rush-hour trips heading to city center; Zheng et al. (2009) studied car-sharing in a university campus) and more research would certainly be needed to offer broader insights. In addition, there were two other studies aiming at assessing the choice between electric and hybrid vehicle types within a car-sharing system (Zoepf and Keith, 2016; Wielinski et al., 2017), which should also be acknowledged.

Overall, the existing studies offered valuable insights on car-sharing choice behavior, though more effort is needed to disclose the modal substitution pattern hidden behind a potential increase of car-sharing's demand. This research aims to contribute to such an understanding by looking at people's short-term mode choice behavior. Specifically, we would like to investigate how policy interventions could effectively step in and make car-sharing a more appealing choice among various daily mobility options. As a result, we will first study the car-sharing choice behavior using a mode choice analysis and then evaluate the modal substitution pattern via a simulation analysis. In particular, policy implications will be derived from the latter part of the work, in which different measures aiming at promoting car-sharing usage will be proposed and their effects on modal substitution pattern will be assessed.

The work presented in this paper involves a case study in a Chinese city, Taiyuan, which has more than 3 million citizens and operates a successful bike-sharing system. In China, the concept of car-sharing has gained tremendous attention recently (Hao, 2017; Xinhua, 2017) though a few small schemes have existed in several cities for a longer time. A stated preference (SP) survey was launched in 2015 to study the mode choice behavior of Taiyuan citizens towards a potential car-sharing service and other existing modes. Data was collected separately for medium-distance ("mid-dist", 2km to 5km) trips and long-distance ("long-dist", more than 5km) trips[1]. In this work, we develop models and generate results separately for the two trip cases to see if the modal substitution pattern would differ by distance. The modeling approach that we use is mixed nested logit (Hess et al., 2004) in order to address both inter-alternative correlation and panel effect, while avoiding the confounding effect when accommodating the two issues in a mixed multinomial logit model (Cherchi, 2009; Ortúzar and Willumsen, 2011). Revealed preference (RP) data is also introduced to perform a joint analysis with the SP data. The combination of the two types of data will help to correct each other's weakness and increase the credibility of model estimation results (Hensher and Bradley, 1993; Ben-Akiva et al., 1994).

Overall, the findings are expected to offer an insight to the puzzle that if more people choosing car-sharing "reduces the use of private vehicles or if, on the contrary, it reduces the number of public transport users" (Jorge and Correia, 2013), from a short-term perspective. Policy makers can clearly see the modal substitution pattern as a result of different measures that they could possibly adopt to promote car-sharing usage, and meanwhile, policy options that could more effectively bring down private car usage will also be identified in the end.

The paper is structured as follows. Section 2 explains the data source, followed by the modeling framework in section 3. Section 4 presents the model estimation results and based on which a number of informative indicators (e.g. willingness to pay for travel time savings, direct and cross point elasticity) are derived. The policy impact analysis and relevant discussion are given in section 5. Section 6 concludes the paper.

2. CASE STUDY AND DATA

The authors designed a paper-based questionnaire survey to collect both SP and RP mode choice data, as well as socio-economic information, from the citizens of a Chinese city, Taiyuan. It is the capital city of Shanxi, a northern province in the country. More than 3 million people live in the urban area of this city. In particular, a bike-sharing system, which was introduced in 2012 and operated by the local government, has won great international reputation owing to its huge success (Burkholder, 2015; Hiles, 2015). Car-sharing, on the other hand, is not yet a travel option in Taiyuan. However, given the nationwide attention that has been drawn upon car-sharing over the recent time in China (Hao, 2017; Xinhua, 2017) the service is expected to enter Taiyuan in near future. Thus, one of the objectives of our survey is to capture the mode choice behavior towards car-sharing in order to be prepared for its future deployment in the city[2].

We designed an SP mode choice experiment in our survey to fulfill this requirement. The

[1] They are named as "medium" and "long" distances because the survey also collected short-distance (within 2km) trip data. However, < 2km trips are excluded from this research since car-sharing is not expected to be competitive within such a distance due to the associated access and alighting time (Martinez et al., 2017).

[2] Recall the strategic-tactical choice framework in Le Vine et al. (2014), our survey did not address the strategic-level car-sharing choice behavior; this is because most car-sharing services in China do not require regular membership fee/long-term commitment, which makes the effect of strategic choice trivial.

experiment presented to each individual respondent hypothetical daily trip scenarios and asked them to choose which transport mode they would use. Hence, it offers a way to capture the choice of car-sharing, even if the service was not yet available in Taiyuan at the time of the survey. In fact, it is also a useful technique for deriving wider policy implications, as SP data usually captures "a wider and broader array of preference-driven behaviors" (Louviere et al., 2003; p. 231) than the conventional RP data.

Nevertheless, before we came up with the final design of the SP experiment, we conducted a pilot survey, which aimed to help us identify what elements need to be incorporated in the SP scenarios. Around 150 Taiyuan citizens participated during the pilot phase and provided with their opinions on the questionnaire design.

The first important insight that we gained from the pilot survey was the need to have different SP scenarios based on the distance travelled; this was an outcome both from analyzing the RP trip diary data and from the comments made by the participants. In particular, we observed that when distances went beyond 2km, the number of walking trips dropped substantially whereas when distances went below 2km, taxi trips were rarely seen. In light of such rather distinct trends, we decided to split the scenarios in our SP survey by trip distance and assign different choice sets accordingly, i.e. making "walk" available only for short trips (within 2km) and making "taxi" available only for longer trips (over 2km) to approximate the mode choice situation towards a real-life case. Moreover, by hearing from participants describing their daily travel experience in Taiyuan, we further split the trips over 2km to "between 2km and 5km" and "more than 5km" to reflect what local people perceive as a medium-distance (mid-dist) trip and a long-distance (long-dist) trip for moving around in the city. In fact, such a split has also helped us identify if the mode choice behavior and modal substitution pattern would differ by distance, and hence yield more targeted insights for policy take-away (see the mode choice analysis later on in this work).

As explained earlier, this research uses data from mid- and long-dist trips to study car-sharing choice. Thus, for these two distance cases, we included six alternatives in the choice set: 1. car-sharing, 2. car, 3. taxi, 4. bus, 5. electric bike and 6. bike-sharing, which represent all the urban transport modes that are frequently used by Taiyuan citizens (except car-sharing[3]). In particular, walking is excluded as per our discussion above on trip distance; while private bike is also excluded due to its continuously decreasing usage as a result of the continuous expansion of the city's bike-sharing program.

The SP experimental design for mid- and long-dist trips is shown in Table 1. Each of the aforementioned alternatives possesses several mode-specific attributes, with trip purpose, temperature, weather and air pollution as the external conditions. Apart from doing a literature review, the selection of these attributes was also based on findings from the pilot survey. For instance, the "Walking time to/from station" was included after observing some potential connections (though we did not test the correlation) between respondents' stated walking times to/from bus or bike-sharing stations and whether any bus or bike-sharing trips were made in the RP diary; similarly, "Mobile app availability" was captured by seeing in the socio-economic part of the survey, that quite a few individuals stated they would use smartphone to call taxi and check real-time bike-sharing information. Besides, the pilot survey results also helped derive the levels/values for some of the attributes. For example, to generate the possible travel time and travel cost values for each alternative mode, we adopted the observed average values from the trip diary part of the pilot survey and multiplied by ±10%, ±20% etc. Although, due to the lack of official trip

[3] As per the pilot survey feedback there was imperfect knowledge among Taiyuan citizens about what car-sharing really represents. Thus, the concept and key features of a free-floating car-sharing scheme were described in the survey to reduce the bias in their understanding.

diary data we are not able to make a comparison for our observed travel times and costs, we still expect the values can be trusted given the sample size we had for the pilot survey. In addition, we discussed with experts from the local transport authorities to make sure the attribute values were generated on reasonable scales. Appendix A gives an example of a mid-dist scenario and a long-dist scenario as seen by survey participants.

TABLE 1 SP Survey Design, Mid- and Long- distance Trips

Mid-dist						
Trip purpose: work/education, leisure, shopping. **Weather:** sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°). **Air pollution level:** excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.						
	Car-sharing	**Car**	**Taxi**	**Bus**	**Electric bike**	**Bike-sharing**
Travel time	5, 10, 15, 20, 25min.	5, 10, 15, 20, 25min.	5, 10, 15, 20, 25min.	10, 12, 15, 20, 25, 30min.	8, 10, 12, 15, 20 min.	12, 15, 20, 25, 30 min.
Travel cost*	￥3, 5, 8, 10, 15, 20	￥1.8, 2, 2.5, 3, 3.5, 4, 5	￥10, 12, 15, 18, 20, 25, 30	￥0.5, 1, 1.5, 2, 2.5		￥0, 0.5, 1, 1.5
Parking space		Easy/hard to find parking				
Parking cost*		Free, ￥2/h, ￥5/h, ￥8/h.				
Walking time to/from station	5min, 10min, 15min.			5min, 10min, 15min.		2, 5, 10 min.
Bus Frequency				Every 2min, 5min, 10min, 15min.		
Mobile app availability	Yes, no.		Yes, no.	Yes, no.		Yes, no.
Long-dist						
Trip purpose: work/education, leisure, shopping. **Weather:** sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°). **Air pollution level:** excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.						
	Car-sharing	**Car**	**Taxi**	**Bus**	**Electric bike**	**Bike-sharing**
Travel time	15, 20, 25, 30, 40min.	15, 20, 25, 30, 40min.	15, 20, 25, 30, 40min.	15, 20, 30, 40, 50, 60min.	20, 30, 40, 50, 60min.	30, 45, 60, 75, 90, 120min.
Travel cost*	￥10, 15, 20, 25, 30, 40	￥5, 8, 10, 12, 15, 18, 20	￥15, 20, 25, 30, 40, 50	￥0.5, 1, 1.5, 2, 2.5		￥0, 1, 1.5, 2, 3
Parking space		Easy/hard to find parking				
Parking cost*		Free, ￥2/h, ￥5/h, ￥8/h.				
Walking time to/from station	5min, 10min, 15min.			5min, 10min, 15min.		2, 5, 10 min.
Bus Frequency				Every 2min, 5min, 10min, 15min.		
Mobile app availability	Yes, no.		Yes, no.	Yes, no.		Yes, no.

* ￥1 ≈ $0.15

In light of the attributes and attribute levels that have been obtained, theoretically, SP scenarios could then be generated following a full factorial design (Hensher et al., 2005). However, in many cases (ours as well), it would produce an endless number of scenarios which result in a need to embrace a fractional factorial design by extracting only a group of scenarios from the full set. The practice we followed to extract the scenarios for this survey was commonly known as orthogonal design[4] which could help reduce the correlation between the attribute levels. More specifically, we adopted an "orthogonal main effects" design by assuming no interaction effects exist across the attributes, though it is an assumption that can hardly be tested in reality (Hensher et al., 2005; chapter 5.2.3). In order to preserve orthogonality, the key task is to identify the required degree of freedom (DoF), or in other words, the minimum number of scenarios that needs to be extracted (Caussade et al., 2005). By assuming main effects only, we calculated the required DoF for each of the distance cases by following the procedure explained in Louviere et al. (2003) and Hensher et al. (2005). As a result, we had a DoF of 56 for the short-dist scenarios and 58 for the mid- and long-dist scenarios.[5] Thus, for each of the three distance cases, we chose to generate 60 different scenarios and the software we used is SPSS, which can ensure the process of scenario generation preserves orthogonality (Hensher et al., 2005). Next, to further reduce the number of scenarios presented to a respondent, the 60 scenarios in each case were assigned to 30 blocks, and hence, a group of 2 scenarios would be presented in one questionnaire making in total 6 of them by presenting all three distance cases, i.e. two for short-dist trips, two for mid-dist trips, and two for long-dist trips.[6] Eventually, one out of every 30 respondents would be given the same set of SP scenarios in our survey.

Eventually, the survey was launched in summer 2015 with the support from Shanxi Transportation Research Institute, which provided 15 researchers assisting with the questionnaire distribution, questionnaire collection and incorporation of the data into electronic datasets. 2-stage stratified sampling was used by first considering the population distribution in Taiyuan's six districts and second considering the gender distribution within each district. In total, 15,000 Taiyuan citizens were asked to participate in the survey.

The collected data was cleaned by first removing missing and invalid responses. 9,499 out of the 15,000 individuals still remained in the sample after this step. Then, the SP choice data used for this paper was further refined by keeping only observations that were rigorously consistent with the participants' RP mode choice information, which was collected in our trip diary survey. For instance, if someone made choices in the mid-dist SP scenarios but did not reveal any 2km~5km trips in his/her trip diary, these SP choices would be excluded from the analysis. The same rule applies to long-dist trips. As a result, we have 3,698 individuals with 6,848 valid SP observations left for mid-dist trips and 6,317 individuals with 11,925 valid SP observations left for long-dist trips.

Table 2 displays the key statistics of the 3,698 and 6,317 individuals, alongside their SP mode choice patterns. The corresponding RP mode choices under the two distance cases are followed in Table 3 by having a slightly different set of alternatives (i.e. with private bike and no car-sharing, as explained above). For socio-economic characteristics, the statistics of age and occupational status demonstrate that adults with fixed jobs constitute the main group in the sample, indicating that the sample has successfully captured regular commuters whose mode choice

[4] Although an orthogonal design is not as advanced as several later proposed designs, such as the various forms of D-efficient design (Bliemer et al., 2009; Rose and Bliemer, 2009; Bliemer and Rose, 2010), we still employed this technique given the constraints we had on project cost (i.e. more advanced software such as Ngene is usually needed to handle an efficient design).
[5] The difference is due to there are different number of attributes between short-dist scenarios and mid- & long-dist scenarios as a result of the different choice sets involved.
[6] We also tested how many choice tasks being presented in the SP experiment were acceptable to respondents. In the pilot survey we included 10 for each individual to answer, and we found most respondents were averse to a number of scenarios larger than 8.

behaviors are highly important to urban planning and policy making.

TABLE 2 Sample Statistics and SP Modal Splits

		Mid-dist (N=3,698)	Long-dist (N=6,317)
Gender	Male	51%	52%
	Female	49%	48%
Age	under 18	7%	5%
	18-25	31%	25%
	26-35	27%	32%
	36-45	22%	26%
	46-59	11%	11%
	60 or above	2%	1%
Marital status	Single	45%	37%
	Married	55%	63%
Educational level	High school or below	27%	25%
	College	35%	33%
	Undergraduate	33%	36%
	Graduate and above	5%	6%
Occupational status	Fixed job	68%	76%
	Student	24%	16%
	Retired	2%	1%
	Self-employed or unemployed	6%	7%
Public transport card	Percentage of possession	74%	79%
Cycling capability	Health enough to cycle	95%	94%
Household monthly income (after tax)	Under ￥3000	34%	28%
	￥3000 -￥6000	38%	40%
	￥6000 -￥9000	15%	18%
	￥9000 -￥15000	8%	9%
	￥15000 -￥30000	3%	3%
	Over ￥30000	2%	1%
Household car	Percentage of possession	45%	55%
Household electric bike	Percentage of possession	46%	46%

SP Modal splits in mid- and long-dist trips					
Car-sharing	**Car**	**Taxi**	**Bus**	**Electric bike**	**Bike-sharing**
					Mid-dist: 6,848 obs.
19%	13%	8%	36%	12%	12%
					Long-dist: 11,925 obs.
19%	24%	9%	32%	9%	7%

TABLE 3 RP Modal Splits in Mid- and Long-dist Trips

Mid-dist (4,807 obs.)		**Long-dist (9,899 obs.)**	
Car*	16%	Car*	28%
Taxi	5%	Taxi	7%
Bus	46%	Bus	40%
Electric bike	17%	Electric bike	14%
Bike-sharing	11%	Bike-sharing	9%
Bike	5%	Bike	2%

* It is also revealed by the trip diary survey that the mid-dist car trips consist of 11% car driver trips and 5% car passenger trips; the long-dist car trips consist of 20% car driver trips and 8% car passenger trips.

3. MODELING FRAMEWORK

Mixed nested logit (mixed NL) models are used to separately study mid- and long-dist mode choice data. There are two dimensions that such a complex modeling structure is found superior to a standard multinomial logit (MNL) model: accommodating inter-alternative correlation and panel effect. Inter-alternative correlation means several alternatives could possibly share common but unobserved attributes. Panel effect would normally occur in an SP survey when an individual was presented with more than one choice task (as in our case). Both issues, if not being addressed properly, would bias the model estimation results. Traditionally, a closed-form nested logit (NL) model could address inter-alternative correlation while a more flexible mixed MNL model could address both issues (McFadden and Train, 2000; Hensher and Greene, 2003). Nevertheless, researchers also discovered that confounding effect could arise when more than one type of such error component was involved in a mixed MNL model (Hess et al., 2004). Hence arguments have come forward preferring a mixed NL structure in order to use the nested part to represent inter-alternative correlation and the integration over mixture distributions to capture the other error component (Ortúzar and Willumsen, 2011). The mathematical formulation of a mixed NL structure is described below:

The utility function for an alternative i ($i \in C_n$) chosen by an individual n ($n = 1,...,N$) at the t^{th} ($t = 1,...,T$) number of SP scenario is given by:

$$U_{int} = \sum_{k=1}^{K} \beta_k X_{intk} + \sigma_i \eta_{in} + \varepsilon_{int} \qquad (1)$$

while the part that can be explained by the model is:

$$V_{int} = \sum_{k=1}^{K} \beta_k X_{intk} + \sigma_i \eta_{in} \qquad (2)$$

where C_n is the choice set, U is the utility associated with a mode choice, X is the vector of explanatory variables and the normally distributed error component η with zero mean captures the panel effect. The estimated parameters are β_k and σ. V is the measurable utility and ε is the unobserved term i.i.d. Extreme Value and independent from η.

The choice probability functions are:

Choice of a nest (upper level):

$$P_{M_s nt} = \frac{e^{\lambda_s IV_{snt}}}{\sum_{z=1}^{Z} e^{\lambda_z IV_{znt}}} \qquad (3)$$

Choice of an alternative inside a nest (lower level):

$$P_{int|M_s} = \frac{e^{V_{int}/\lambda_s}}{\sum_{j \in M_s} e^{V_{jnt}/\lambda_s}} \qquad (4)$$

General choice of an alternative:

$$P_{int} = P_{M_s nt} P_{int|M_s} \quad (5)$$

where P is choice probability, M_s represents the nest s ($s = 1,...,z$), IV is the expected maximum utility for the choice of alternatives inside a nest, λ is the scale parameter measuring the different variances across nests.

The general choice probability function is integrated over η, gives (now P_{int} is fully denoted as the conditional probability $P_{nt}(i_t \mid X_{int}, \beta_k, \eta_{in}, C_n)$):

$$L_n(i \mid X_{in}, \beta_k, \sigma_i, C_n) = \int \prod_{t=1}^{T} P_{nt}(i_t \mid X_{int}, \beta_k, \eta_{in}, C_n) f(\eta_{in}) d\eta_{in} \quad (6)$$

Log-likelihood function that needs to be maximized:

$$LL(\beta, \eta) = \sum_{n=1}^{N} \sum_{i \in C_n} y_{in} InL_n(i \mid X_{in}, \beta_k, \sigma_i, C_n) \quad (7)$$

where y_{in} takes the value of 1 if an individual n chooses an alternative i and 0 otherwise.

The variables that were included in the final models are listed in Table 4. Each explanatory variable was tested by its effect on all mode choice utilities and the one which showed minimum effect (in terms of absolute value) was normalized to zero. Highly insignificant variables were removed from the utility functions to avoid type I error[7]. Several issues are worth mentioning: Air pollution was presented in categorical measures to survey participants; however, the categories were defined based on the air quality index (AQI) scheme as shown in Table 4. Thus, we modeled air pollution as a continuous variable, a preferred way of measurement in choice modeling (Ben-Akiva and Lerman, 1985; Moudon et al., 2005). Temperature was tested by a linear (continuous variable) and a curvilinear (dummy variable 1 for extreme temperature and 0 otherwise) relationship respectively for its effect on mode choice utilities; the former type of correlation was adopted due to higher t-statistics. Generic parameters on travel time and cost were tested against alternative specific parameters. The use of generic parameters reduced model fitness in terms of likelihood ratio test and adjusted rho-bar squared, and thus alternative specific parameters for travel time and cost were eventually applied. Systematic taste heterogeneity (i.e. how different socio-economic groups think of different attributes) has been a popular way to study socio-economic impacts (Amador et al., 2005; Cherchi and Ortúzar, 2002; Cherchi and Ortúzar, 2011). Our final models adopted such a form also due to the resulted higher values on model fitness comparing to directly adding the socio-economic variables in utility functions. Moreover, after testing with the socio-economic variables in their original sub-grouping formats, we merged the sub-groups of each variable into two general groups (i.e. low and high) to more clearly manifest the impacts. In the end, availability conditions were considered in the mode choice models: 1. Car is available to households that own a car[8], 2. Electric bike is available to households that own an electric bike, and 3. Cycling is available to those who are able to cycle given their state of health. These conditions increased model validity by helping to explain the circumstances

[7] However, insignificant "policy variables" (or, level of service variables, such as travel times, travel costs, access times and app availability) are still included in light of the discussions in Ortúzar and Willumsen (2011).
[8] Possession of a driving license is not an availability condition in this case since we allow the choices of car and car-sharing to come from both drivers and passengers.

within which someone did not choose a particular mode due to the fact that the mode was not an available option.

The above analysis was first applied on the mid- and long-dist SP datasets. Then we formed up a pooled dataset for each distance case by bringing in the respondents' RP trips conducted in the same distance range. The critical limitation of SP data is it only captures hypothetical choice behavior which may be inconsistent with choices that would be made in real life (Louviere et al., 2003). The joint analysis of the two types of data could reduce the behavioral bias and many works have followed such a practice (Hensher and Bradley, 1993; Ben-Akiva et al., 1994; Bradley and Daly, 1997; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011; Lavasani et al., 2017). In our case, although the RP data did not capture car-sharing choice as well as a few other variables (air pollution, temperature, parking cost and space, access time and app availability due to paper-based survey) it could still help with the rest parameter estimation and improve the overall model fitness. Thus, in each of the two distance cases, we conducted the mixed NL analysis on the pooled dataset in order to have a comparison to the model performance based on SP data. Different scaling factors were applied in the joint SP/RP model estimation to address the difference in the variances of the unobserved error terms across the two datasets. Since SP data is the primary source in this study, the RP utilities were scaled relative to it.

In the end, many hypotheses have been proposed prior to the modeling analysis including a few relevant to car-sharing: longer travel time and higher travel cost could both decrease the probability to choose car-sharing, longer walking time to car-sharing spots would also decrease the utility of using car-sharing service, whereas a smartphone based application would make car-sharing more appealing and more likely to be chosen.

TABLE 4 Explanatory Variables and Measurements

Variable	Measurement
Air pollution	air quality index (AQI) by taking the average value of each level (25 for excellent level '0-50', 75 for good level '51-100', 125 for light pollution '101-150', 175 for medium pollution '151-200', 250 for heavy pollution '201-300', 400 for terrible pollution 'above 300')
Rain	1 if weather is rainy, 0 if otherwise
Temperature	temperature in °C
Commute	1 if trip purpose is commute (i.e. work/education), 0 if otherwise
Travel cost	in RMB (￥)
Parking cost	in RMB (￥)/hour
Parking space	1 if available, 0 otherwise
Travel time	in min
Access time	in min, walking time to stations/parking spots
Waiting time	in min, waiting time at bus stop
App availability	1 if a smart phone application is available, 0 otherwise
Male	1 if gender is male, 0 if female
Lower age	1 if age is "under 18" or "18-25" or "26-35", 0 if "36-45" or "46-59" or "60 or above"
Lower income	1 if household monthly income is "under ￥3000" or "￥3000-￥6000" or "￥6000-￥9000", 0 if "￥9000-￥15000" or "￥15000-￥30000" or "over ￥30000"
Lower education	1 if educational level is "high school or below" or "college", 0 if "undergraduate" or "graduate and above"

4. RESULTS

Table 5 and 6 present the mixed NL results which were generated using PythonBiogeme

(Bierlaire, 2016). More information is available in Appendix B showing the results of the corresponding NL models before we applied the mixed structure.

In both mid- and long-dist trips, the joint SP/RP model offers improved values in likelihood ratio test and adjusted rho-bar squared comparing to the model using only SP data. The choice behavior as being revealed by SP and SP/RP datasets are very much consistent in terms of the observed signs of impact[9]. We, therefore, base our discussion only on the results of the joint SP/RP model for both distance cases. In particular, factors affecting car-sharing choice and private car choice are discussed in detail. Their coefficients are inspected first, followed by an exploration of willingness to pay for travel time savings and an elasticity analysis with respect to a number of key variables.

In Table 5 and Table 6, the impacting factors are classified into three types: natural environmental conditions, trip and mode attributes and systematic taste heterogeneity. As far as natural environmental conditions, car-sharing and private car are the significantly preferred choices when air pollution level increases. This is possibly due to the sealed space and more protected environment they could offer to users who want to stay away from pollution. As a comparison, weather conditions are not that strongly associated with the choice of car or car-sharing. In mid-dist trips, neither of them is significantly affected by rain or temperature (results not presented due to high insignificance); however, in long-dist trips, car is preferred when there is rain and car-sharing is more likely to be chosen in colder temperature. The results potentially imply a correlation between weathers' effects and trip distance, such that when a trip becomes longer, travellers may start to care more about the weather conditions.

With regard to trip and mode attributes, travel time and cost both negatively affect the probabilities to choose car-sharing and car in mid- and long-dist trips. Both findings are consistent with microeconomic theory. However, not all parameter values appear to be significant, i.e. travel time's impact on both car and car-sharing in mid-dist trips and travel cost's impact on car-sharing in long-dist trips. More insights on significance level are discussed later alongside the estimation of willingness to pay for travel time savings. Next, the four mode-related attributes that were only captured by the SP survey [car parking cost (negative), car parking space (positive), car-sharing access time (negative) and car-sharing app availability (positive)] all have the expected impact signs to our hypothesis, although parking space is much less significant in affecting car choice in both distances. The results could bring some direct implications for policy making; specifically, reducing the walking time to car-sharing spot and introducing smartphone application to car-sharing service could both help improve the usage of car-sharing, while raising the parking cost would be useful in suppressing private car demand. At last, in mid-dist trips, car-sharing is revealed as a preferred mode for non-commute purposes; meanwhile, in long-dist trips, the service is preferred for commute use. Private car choice is not found with significant correlation with any of the trip purposes.

Systematic taste heterogeneity offers more in-depth insight on socio-economic impact. For a car-sharing alternative, a number of interaction terms are detected with significance. The lower education group is not keen on using car-sharing service even when air pollution levels are high, which could make the service more attractive. The lower age group seems to prefer car-sharing even when car-sharing becomes less appealing in warmer weather. The former discovery is statistically significant in the mid-dist case and the latter is in the long-dist case. Moreover, despite car-sharing is generally preferred for commute in long-dist trips and not preferred in mid-dist trips, the lower education group is, in particular, less likely to use the service for commute in both cases.

[9] The only exception is observed on the impact of trip purpose. When RP data is involved, bike-sharing is no longer a preferred mode for mid-dist commute trips while taxi and bus are no longer among the preferred modes for long-dist commute trips.

Additionally, in the long-dist case, the interaction between temperature and gender group is also captured but presented with statistical insignificance. This is due to the effect was initially found significant in the NL structure; however, it became insignificant after the mixed NL structure incorporates panel effect which could better explain the model. As for private car alternative, no significant taste heterogeneity is discovered in mid-dist trips; in long-dist trips, the lower income and lower education groups would value less the increased utility of car resulted from increased air pollution level, which looks similar to what we found for car-sharing. As a summary, less wealthy and less educated people may be less likely to use car-sharing and private car; younger group seems to prefer car-sharing, however, this is only indicated by one significant interaction term; gender effect is negligible.

Factors affecting other mode choices are not discussed in detail given the scope of this work and readers are invited to see them directly from Table 5 and 6. Overall, all factors have the expected signs of impact, though a few of them appear statistically insignificant.

At last, inter-alternative correlation and panel effect are captured by the mixed NL structure of our models. Different nests are identified for mid- and long-dist trips. In the former case, the nest ‘self-driven automobile’ including car-sharing and car is found significant while in the latter case, car-sharing and bike-sharing are found to have significant correlation under the nest ‘sharing economy’. Both nests come from the SP part of the data. Other possibilities have also been tested such as car-sharing, car and taxi under ‘comfortable automobile’, car-sharing, taxi and bus under ‘shared automobile’, electric bike and bike-sharing under ‘two-wheeled vehicle’ as well as bike-sharing and bike under ‘active transport’ when RP data is also involved. However, none of these nests was found with significance[10]. It should also be noted that the nesting parameter μ is larger than 1 in all the models. Such a value range satisfies the specification requirement of nested logit (Hess et al., 2004; Ortúzar and Willumsen, 2011) where $\mu = 1/\lambda$ [11]. For panel effect, it is estimated simultaneously by the SP part and the RP part in the pooled datasets, since both of which contain repeated choice observations from a single individual. The effect on all alternatives appears to be significant (note that taxi is normalized) except for the one on private bike in the long-dist case.

TABLE 5 Mixed NL Results for Mid-dist Case

	SP data		SP & RP data	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{carshare}$ (SP)	- 1.76	- 4.70	- 1.88	- 6.51
α_{car} (SP)	- 0.60	- 1.24	- 0.03	- 0.13
α_{taxi} (SP)	- 1.75	- 4.06	- 1.40	- 4.15
α_{bus} (SP)	- 0.18	- 0.43	0.12	0.45
$\alpha_{bikeshare}$ (SP)	4.18	9.62	3.41	11.19
$\alpha_{cardriver}$ (RP)	-	-	0.90	7.16
$\alpha_{carpassenger}$ (RP)	-	-	0.35	2.76
α_{taxi} (RP)	-	-	0.87	5.48

[10] In fact, we found another nest (between car driver and car passenger) using only the RP data, where the t-statistic also shows significance; however, the nesting parameter μ has a value of 1.03 which is almost equivalent to an MNL specification. Thus, we discarded this nest by following the practice of Ortúzar and Willumsen (2011), in order to retain efficiency in model estimation.

[11] λ was defined earlier in Eq. 3 and Eq. 4.

α_{bus} (RP)	-	-	1.17	7.62
α_{ebike} (RP)	-	-	0.68	4.07
α_{bike} (RP)	-	-	0.04	0.16
Natural environmental conditions				
Air pollution-carshare (SP)	0.0109	6.98	0.0089	7.42
Air pollution-car (SP)	0.0041	2.54	0.0026	2.64
Air pollution-taxi (SP)	0.0032	1.86*	0.0005	0.43**
Air pollution-bus (SP)	0.0009	0.59**	0.0008	0.76**
Air pollution-bikeshare (SP)	- 0.0243	- 11.12	- 0.0202	- 12.88
Rain-ebike (SP & RP)	- 1.02	- 3.49	- 0.45	- 4.31
Temperature-taxi (SP)	- 0.02	- 3.02	- 0.01	- 2.21
Temperature-ebike (SP)	0.05	4.58	0.03	4.07
Trip and mode attributes				
Commute-carshare (SP)	- 0.78	- 3.77	- 0.54	- 3.16
Commute-taxi (SP & RP)	- 1.39	- 5.92	- 0.28	- 4.82
Commute-ebike (SP & RP)	0.92	5.28	0.18	3.86
Commute-bikeshare (SP & RP)	0.61	3.25	- 0.06	- 1.40**
Travel cost-carshare (SP)	- 0.03	- 1.95*	- 0.04	- 2.86
Travel cost-car (SP & RP)	- 0.15	- 0.82**	- 0.07	- 2.33
Travel cost-taxi (SP & RP)	- 0.08	- 4.66	- 0.04	- 3.34
Travel cost-bus (SP & RP)	- 0.02	- 0.15**	- 0.02	- 2.21
Travel cost-bikeshare (SP & RP)	- 0.41	- 3.18	- 0.55	- 5.59
Parking cost-car (SP)	- 0.14	- 4.93	- 0.05	- 3.50
Parking space-car (SP)	0.17	0.91**	0.07	0.69**
Travel time-carshare (SP)	- 0.03	- 2.59	- 0.01	- 1.32**
Travel time-car (SP & RP)	- 0.02	- 0.76**	- 0.01	- 1.11**
Travel time-taxi (SP & RP)	- 0.01	- 0.07**	- 0.01	- 1.44**
Travel time-bus (SP & RP)	- 0.04	- 3.36	- 0.01	- 0.52**
Travel time-ebike (SP & RP)	- 0.05	- 3.09	- 0.02	- 1.62**
Travel time-bikeshare (SP & RP)	- 0.18	- 9.85	- 0.19	- 13.81
Travel time-bike (RP)	-	-	- 0.01	- 0.06**
Waiting time-bus (SP)	- 0.03	- 2.07	- 0.03	- 2.88
Access time-carshare (SP)	- 0.02	- 1.08**	- 0.04	- 2.49
Access time-bikeshare (SP)	- 0.37	- 10.45	- 0.24	- 10.91
App availability-carshare (SP)	0.35	3.23	0.36	3.79
App availability-taxi (SP)	0.36	2.18	0.28	2.04
App availability-bus (SP)	0.11	0.93**	0.14	1.77*
App availability-bikeshare (SP)	3.79	10.69	3.63	12.09

Systematic taste heterogeneity				
Air pollution * Male-bus (SP)	- 0.0028	- 4.15	- 0.0017	- 3.43
Air pollution * Lower age-taxi (SP)	0.0027	3.08	0.0032	3.83
Air pollution * Lower age-bus (SP)	0.0042	5.33	0.0029	5.20
Air pollution * Lower education-carshare (SP)	- 0.0040	- 4.03	- 0.0025	- 2.85
Air pollution * Lower education-taxi (SP)	- 0.0036	- 3.34	- 0.0008	- 1.13**
Commute * Lower education-carshare (SP)	- 0.54	- 2.47	- 0.38	- 1.98
Commute * Lower education-taxi (SP & RP)	- 0.53	- 2.02	- 0.09	- 1.08**
Inter-alternative correlation & Panel effect				
$\mu_{selfdriven}$ (SP)	1.93	8.17#	1.44	7.26#
$\sigma_{carshare}$ (SP & RP)	1.20	8.84	1.66	15.92
σ_{car} (SP & RP)	2.92	11.41	0.63	7.41
σ_{bus} (SP & RP)	1.95	18.13	0.89	13.40
σ_{ebike} (SP & RP)	2.53	12.61	1.35	12.50
$\sigma_{bikeshare}$ (SP & RP)	1.24	6.10	0.89	9.95
σ_{bike} (RP)	-	-	1.04	5.56
Scaling factor (RP)	-	-	7.65	10.03#
Number of observations	6848		11655	
Initial log-likelihood	- 10738.4		- 15408.3	
Final log-likelihood	- 8523.9		- 11342.9	
Likelihood ratio test	4428.9		8130.7	
Adjusted rho-bar squared	0.20		0.26	

The brackets of (SP), (RP) and (SP & RP) should only be referred to when checking the results based on the pooled SP/RP data.

Note also: * parameter values not meeting the 95% significance level

** parameter values not meeting the 90% significance level

t-test against base value of 1

TABLE 6 Mixed NL Results for Long-dist Case

	SP data		SP & RP data	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{carshare}$ (SP)	- 3.45	- 5.46	- 3.36	- 10.52
α_{car} (SP)	- 1.12	- 1.95	- 1.29	- 5.61
α_{taxi} (SP)	- 1.00	- 1.86	- 0.68	- 3.48
α_{bus} (SP)	3.97	7.19	2.40	10.09
α_{ebike} (SP)	0.01	0.01	- 1.34	- 5.20
$\alpha_{cardriver}$ (RP)	-	-	- 2.75	- 16.97

$\alpha_{carpassenger}$ (RP)	-	-	- 3.10	- 18.64
α_{taxi} (RP)	-	-	- 1.73	- 14.36
α_{bus} (RP)	-	-	- 0.69	- 6.06
α_{ebike} (RP)	-	-	- 2.44	- 12.38
α_{bike} (RP)	-	-	- 1.17	- 8.10
Natural environmental conditions				
Air pollution-carshare (SP)	0.0102	15.90	0.0077	14.52
Air pollution-car (SP)	0.0102	9.39	0.0073	9.72
Air pollution-taxi (SP)	0.0067	13.25	0.0071	15.77
Air pollution-bikeshare (SP)	- 0.0254	- 6.25	- 0.0070	- 5.62
Rain-car (SP & RP)	0.36	1.54**	0.33	3.46
Rain-taxi (SP & RP)	0.33	2.06	0.30	4.50
Rain-bus (SP & RP)	0.24	1.91*	0.04	0.51**
Rain-ebike (SP & RP)	- 0.89	- 5.11	- 0.61	- 4.69
Rain-bikeshare (SP & RP)	- 1.03	- 3.67	- 0.15	- 1.90*
Temperature-carshare (SP)	- 0.06	- 6.26	- 0.04	- 5.10
Temperature-taxi (SP)	- 0.04	- 6.08	- 0.03	- 4.98
Temperature-bus (SP)	- 0.07	- 9.60	- 0.06	- 9.42
Temperature-bikeshare (SP)	0.05	3.83	0.01	0.24**
Trip and mode attributes				
Commute-carshare (SP)	1.84	9.63	0.98	7.01
Commute-taxi (SP & RP)	0.27	1.79*	- 0.63	- 11.78
Commute-bus (SP & RP)	0.03	0.18**	- 0.58	- 6.49
Commute-bikeshare (SP & RP)	- 2.94	- 5.76	- 0.96	- 13.35
Travel cost-carshare (SP)	- 0.03	- 3.26	- 0.02	- 1.36**
Travel cost-car (SP & RP)	- 0.02	- 0.34**	- 0.06	- 9.04
Travel cost-taxi (SP & RP)	- 0.05	- 5.53	- 0.04	- 12.95
Travel cost-bus (SP & RP)	- 0.96	- 12.59	- 0.32	- 7.00
Travel cost-bikeshare (SP & RP)	- 1.35	- 5.63	- 0.67	- 8.83
Parking cost-car (SP)	- 0.10	- 3.04	- 0.09	- 3.83
Parking space-car (SP)	0.69	2.88	0.19	1.35**
Travel time-carshare (SP)	- 0.08	- 7.06	- 0.03	- 3.53
Travel time-car (SP & RP)	- 0.05	- 1.88*	- 0.04	- 11.04
Travel time-taxi (SP & RP)	- 0.04	- 3.02	- 0.05	- 15.70
Travel time-bus (SP & RP)	- 0.01	- 1.91*	- 0.09	- 5.69
Travel time-ebike (SP & RP)	- 0.06	- 9.68	- 0.04	- 10.88
Travel time-bikeshare (SP & RP)	- 0.07	- 8.51	- 0.38	- 16.44

Travel time-bike (RP)	-	-	- 0.02	- 5.17
Waiting time-bus (SP)	- 0.08	- 6.10	- 0.15	- 12.68
Access time-carshare (SP)	- 0.06	- 4.34	- 0.04	- 3.81
Access time-bus (SP)	- 0.29	- 17.68	- 0.25	- 17.36
Access time-bikeshare (SP)	- 0.11	- 2.27	- 0.01	- 0.29**
App availability-carshare (SP)	1.79	8.33	1.49	10.73
App availability-taxi (SP)	0.20	1.95*	0.29	3.34
Systematic taste heterogeneity				
Air pollution * Male-bikeshare (SP)	0.0053	2.45	0.0019	2.12
Air pollution * Lower income-car (SP)	- 0.0024	- 2.94	- 0.0021	- 3.38
Air pollution * Lower education-car (SP)	- 0.0017	- 2.34	- 0.0009	- 1.69*
Temperature * Male-carshare (SP)	- 0.01	- 1.36**	- 0.01	- 0.90**
Temperature * Male-bus (SP)	- 0.01	- 3.18	- 0.01	- 3.32
Temperature * Lower age-carshare (SP)	0.03	5.30	0.02	4.81
Temperature * Lower age-taxi (SP)	0.03	5.89	0.02	5.29
Commute * Lower income-bus (SP & RP)	0.53	3.63	0.53	5.90
Commute * Lower education-carshare (SP)	- 0.22	- 2.33	- 0.18	- 2.50
Inter-alternative correlation & Panel effect				
$\mu_{sharingeconomy}$ (SP)	2.55	6.26#	1.75	5.31#
$\sigma_{carshare}$ (SP & RP)	1.44	12.53	0.97	7.67
σ_{car} (SP & RP)	4.10	21.15	2.52	21.11
σ_{bus} (SP & RP)	1.66	18.40	1.97	24.57
σ_{ebike} (SP & RP)	2.84	16.06	3.76	18.88
$\sigma_{bikeshare}$ (SP & RP)	3.74	9.19	1.16	10.55
σ_{bike} (RP)	-	-	0.02	0.27**
Scaling factor (RP)	-	-	2.68	19.37#
Number of observations	11925		21824	
Initial log-likelihood	- 18938.3		- 35361.5	
Final log-likelihood	- 14322.4		- 23925.7	
Likelihood ratio test	9231.9		22871.5	
Adjusted rho-bar squared	0.24		0.32	

The brackets of (SP), (RP) and (SP & RP) should only be referred to when checking the results based on the pooled SP/RP data.

Note also: * parameter values not meeting the 95% significance level

** parameter values not meeting the 90% significance level

t-test against base value of 1

By having the results of mode choice models, theoretically, a value of time indicator can be derived to demonstrate how much people are willing to pay for enjoying a reduction of travel time, i.e. often known as the value of travel time savings (VTTS). Such an indicator is often used in transport project appraisals as a measure of the expected monetary benefits to society. The standard way to calculate VTTS would need the measurement of marginal utility of income, and one could use its 'minus' instead, i.e. the coefficient of travel cost in the context of mode choice analysis. Specifically, for linear-in-parameters utility specifications as we have in this research, VTTS is normally derived as the ratio of travel time on travel cost coefficients.

However, a key difference in our case is that alternative-specific travel cost coefficients offered better model performance and were therefore adopted rather than a generic travel cost coefficient, which is the one that could give a consistent measurement of marginal utility of income. As a result, the ratio derived in this research should be viewed differently compared to the standard VTTS. On the one hand, it captures individuals' differentiated tastes on travel costs associated with different modes, and hence can more accurately reflect the trade-off behaviors between time and cost when using different mobility services. In other words, the measure can work better in supporting the policy designs of transport operators, who are interested in understanding how much individuals would be willing to afford a travel cost increase for each unit of their travel time saved (i.e. the substitution pattern between the two factors), and hence making adjustments on prices and levels of service offered. On the other hand, the measure is no longer suitable for project appraisals as a unitary marginal utility of income would be needed in order to quantify the resulted user benefits. Below we present this value for each of the different modes; including car-sharing, private car, taxi, bus and bike-sharing[12] (Table 7).

TABLE 7 Values of Willingness to Pay for Travel Time Savings by Different Mode Users

	Mid-dist	**Long-dist**
Car-sharing	￥22.0 ($3.3)/h	￥81.1 ($12.2)/h
Car	￥6.4 ($1.0)/h	￥43.0 ($6.4)/h
Taxi	￥20.7 ($3.1)/h	￥75.4 ($11.3)/h
Bus	￥21.0 ($3.2)/h	￥51.5 ($7.7)/h
Bike-sharing	￥20.5 ($3.1)/h	￥33.6 ($5.0)/h

Although, strictly speaking, the values in Table 7 should be interpreted differently to the standard VTTS, they are still comparable in between, especially when a number of phenomena are detected and need to get crosschecked in the literature. The key impression from the table is that the values for all modes are higher in long-dist trips than in mid-dist trips. Many studies have found VTTS increasing with trip length and such a finding is supported by microeconomic theory (Wardman, 1998; Axhausen et al., 2008; Shires and De Jong, 2009). In brief, marginal disutility increases as the journey becomes longer so that a travel time reduction in a longer trip is worth more. This also explains the observed increases in t-statistics of travel time's impact on all mode choices from the mid-dist case (Table 5) to the long-dist case (Table 6).

The comparison across modes offers additional insights. Firstly, for mid-dist trips, all the modes share similar values except for car which value is lower than the rest. There are two possible effects that could jointly determine the estimated VTTS for a specific mode (Wardman, 1998;

[12] Electric bike does not involve a perceived travel cost.

Mackie et al., 2003; Shires and De Jong, 2009). One is "user type effect" which means the users of some mode may have different socio-economic characteristics than the users of another mode; for example, car users normally come from higher income groups which often have relatively high VTTS. The other is "mode specific effect" such that the utility of time spent on a mode could affect VTTS; for example, car normally gives more pleasant travel experience in terms of the comfort, cleanliness and privacy it offers, so that the willingness to pay extra in order to save journey time is often weaker than travelling with other modes. Thus, in our case, the lower willingness to pay for car travel time savings could potentially imply the mode-specific effect overwhelms the user type effect.

Next, the results also show that by moving from mid- to long-dist trips, the willingness to pay values for car-sharing, car and taxi increase much more aggressively compared to bus and bike-sharing (recall the value normally increases with trip length). Such a difference is possibly a result of the aforementioned user type effect. As compared to bus and bike-sharing users, the users of car-sharing, car or taxi are found coming from higher education and income groups as per the results shown in Table 5 and 6. Evidence has widely been discovered that people having higher income or being more educated tend to have higher VTTS (Wardman, 1998; Jara-Diaz, 2003; Mackie et al., 2003; Axhausen et al., 2008; Trottenberg and Belenky, 2011). Thus, when the trip length increases as moving from the mid distance to long distance in this case, it might not be surprising to see the surge of willingness to pay with respect to car-sharing, car and taxi which user groups would have stronger incentives to pay extra in order to save travel time.

Finally, as a comparison, Wang and MacKenzie (2017) derived a VTTS value of $9.06/h for the car-sharing service in Seattle though different countries are likely to have different VTTS values (Shires and De Jong, 2009).

In addition, direct and cross point elasticity are calculated with respect to several key attributes of car-sharing and private car. They are car-sharing's travel cost and access time in the mid-dist case; car-sharing's travel time and access time in the long-dist case; private car's travel cost and parking cost in both distances, given their significant impacts as being revealed by the models. "Direct" and "cross" refer to the impact of a change of an alternative's attribute level on the choice probability of the same alternative and of the other alternative respectively (Ben-Akiva and Lerman, 1985). "Point" means elasticity is measured in terms of an infinitesimal level change of an attribute. The estimation procedure is referred to Bierlaire (2017) and the results are given in Table 8.

TABLE 8 Direct and Cross Point Elasticity

	Choice probability of	**Direct**		**Cross**	
Mid-dist	Car-sharing	- 0.197 (TC-carshare)	- 0.188 (AT-carshare)	0.049 (TC-car)	0.014 (PC-car)
	Car	- 0.370 (TC-car)	- 0.119 (PC-car)	0.035 (TC-carshare)	0.030 (AT-carshare)
Long-dist	Car-sharing	- 0.802 (TT-carshare)	- 0.253 (AT-carshare)	0.021 (TC-car)	0.035 (PC-car)
	Car	- 0.059 (TC-car)	- 0.086 (PC-car)	0.180 (TT-carshare)	0.058 (AT-carshare)

Note: "TC" is travel cost, "TT" is travel time, "AT" is access time, "PC" is parking cost

Some trends are clearly revealed:

▪All elasticity values are smaller than one, which means the probabilities of choosing car-sharing and private car are relatively inelastic to the level change of a single attribute. This fits our expectation since mode choice utilities are determined by many attributes altogether with significance, and thus the effect of a single attribute is expected to be limited. Two recent studies (De Luca and Di Pace, 2015; Carteni et al., 2016), which also computed elasticity values for car-sharing and private car, revealed exactly the same range of values.

▪Most of the cross elasticity values (except for changing car-sharing's travel time on the probability to choose private car in the long-dist case) are close to zero, implying that the probability to choose a mode would depend more on its own attribute level changes rather than the attribute level changes of an alternative mode.

More specifically on direct elasticity,

▪For car-sharing, first recall that studying the elasticity on travel cost in the mid-dist case and travel time in the long-dist case is due to their significant impacts as being revealed by the models. It is found that these two attributes are more effective than access time in affecting car-sharing choice probability in both distances.

▪For private car, the choice probability is more elastic to attribute level changes in mid-dist trips than in long-dist trips. This is very much consistent with common perception as car is normally less willing to be substituted when trip distance gets longer. To take a further look, in the mid-dist case, the choice probability is more elastic to a change in travel cost whereas in the long-dist case, it is more elastic to a change in parking cost.

5. POLICY IMPACT ANALYSIS

So far, the results have indicated how individuals' choices would respond to the changes in attribute levels. Nevertheless, an elasticity analysis is still inadequate to help identify the effective ways for promoting car-sharing usage in real practice, especially when the possible degrees of policy intervention could be different across attributes given practical constraints. For instance, it is found in the mid-dist case that the probability of choosing private car is more elastic to a change in travel cost than parking cost. However, the degree that policies are able to adjust car travel cost would usually be smaller than adjusting parking cost. It is because car travel cost (i.e. fuel cost) heavily depends on market oil price whereas parking cost is often a rather local issue and less constrained for adjustment. Thus, which of these two attributes should be the policy focus remains unclear. Our scenario analysis in this section can help to answer such a type of question while revealing other critical insights for policy making. Specifically, we simulate in the SP environment [13] the modal substitution pattern under different policy options that can be implemented in reality. The simulation method is sample enumeration, based on the results derived from the pooled data using mixed NL models. The policy scenarios and corresponding modal splits are displayed in Table 9 for the mid-dist case and Table 10 for the long-dist case.

TABLE 9 Scenarios and Modal Splits for Mid-dist Case

Scenarios

[13] The simulation analysis only aims to reveal how people make trade-offs across the attributes; it does not intend to forecast market demand in the real world.

"Moderate"	A: car-sharing travel cost (-20%), car-sharing access time (-10%)					
"Intermediate"	B1: car-sharing travel cost (-20%), car-sharing access time (-20%)					
"Intermediate"	B2: car-sharing travel cost (-50%), car-sharing access time (-10%)					
"Radical"	C: car-sharing travel cost (-50%), car-sharing access time (-20%)					
"Intermediate" + Complementary Measures	B2 + [D: car travel cost (+10%), car parking cost (+20%)]					
	B2 + [E1: car travel cost (+10%), car parking cost (+50%)]					
	B2 + [E2: car travel cost (+20%), car parking cost (+20%)]					
	B2 + [F: car travel cost (+20%), car parking cost (+50%)]					
Modal splits						
	Car-sharing	Car	Taxi	Bus	Electric bike	Bike-sharing
Baseline	18.8%	13.2%	7.9%	36.2%	12.2%	11.7%
A	20.0%	13.1%	7.7%	35.6%	12.1%	11.5%
B1	20.4%	13.0%	7.7%	35.4%	12.0%	11.5%
B2	21.3%	12.9%	7.6%	34.9%	11.9%	11.4%
C	21.6%	12.9%	7.5%	34.7%	11.9%	11.4%
B2 + D	21.4%	12.2%	7.6%	35.3%	12.0%	11.5%
B2 + E1	21.5%	11.7%	7.7%	35.4%	12.1%	11.6%
B2 + E2	21.5%	11.7%	7.7%	35.4%	12.1%	11.6%
B2 + F	21.6%	11.3%	7.7%	35.6%	12.2%	11.6%

TABLE 10 Scenarios and Modal Splits for Long-dist Case

Scenarios						
"Moderate"	A: car-sharing travel time (-10%), car-sharing access time (-10%)					
"Intermediate"	B1: car-sharing travel time (-10%), car-sharing access time (-20%)					
"Intermediate"	B2: car-sharing travel time (-20%), car-sharing access time (-10%)					
"Radical"	C: car-sharing travel time (-20%), car-sharing access time (-20%)					
"Intermediate" + Complementary Measures	B2 + [D: car travel cost (+10%), car parking cost (+20%)]					
	B2 + [E1: car travel cost (+10%), car parking cost (+50%)]					
	B2 + [E2: car travel cost (+20%), car parking cost (+20%)]					
	B2 + [F: car travel cost (+20%), car parking cost (+50%)]					
Modal splits						
	Car-sharing	Car	Taxi	Bus	Electric bike	Bike-sharing
Baseline	19.0%	23.9%	8.7%	31.0%	9.0%	8.4%
A	21.1%	23.3%	8.4%	30.0%	8.8%	8.4%
B1	21.6%	23.1%	8.3%	29.9%	8.7%	8.4%
B2	22.8%	22.8%	8.1%	29.4%	8.6%	8.3%
C	23.3%	22.6%	8.1%	29.2%	8.5%	8.3%

B2 + D	23.0%	22.2%	8.2%	29.6%	8.6%	8.4%
B2 + E1	23.2%	21.6%	8.3%	29.8%	8.7%	8.4%
B2 + E2	23.0%	22.1%	8.2%	29.6%	8.7%	8.4%
B2 + F	23.3%	21.5%	8.3%	29.8%	8.7%	8.4%

We first target on car-sharing demand promotion by setting up a moderate scenario, two intermediate scenarios and a radical scenario (A, B1, B2 and C). The policy options differ across distances as car-sharing choice is significantly associated with travel cost in the mid-dist case and with travel time in the long-dist case. The impact of access time is significant in both cases. The 20% and 50% travel cost reduction targets can be achieved by receiving subsidies from the public sector; however, a travel time reduction is more difficult to realize. One way to bring down car-sharing's journey time is allowing users to drive on "priority lanes", such as the driving permission for electric cars on bus lanes (BBC, 2016). However, the effect of such a measure cannot be easily predicted and thus, more conservative reduction targets for travel time (i.e. 10% and 20%) are adopted. Access time reduction also adopts relatively conservative targets since it usually requires an increase in the number of parking spots, which is a rather complex task for car-sharing operators.

The modal substitution pattern is different between the two distance cases. In mid-dist trips, car-sharing's market share increases 2.8% (18.8% to 21.6%) from the baseline to the radical scenario (C); in the long-dist case, the increase is 4.3% (19.0% to 23.3%). The difference implies that more people are willing to switch to car-sharing in long-dist trips and such a finding is in line with the discovery that car-sharing becomes more competitive as trips become longer (Martinez et al., 2017). With respect to the usage of other modes (compare the baseline still to C), bus shrinks 1.5% and car shrinks 0.3% in mid-dist trips while bus shrinks 1.8% and car shrinks 1.3% in long-dist trips[14]. The comparison among the figures reveals a challenge for the mid-dist case, i.e. private car usage is not reduced when car-sharing becomes more attractive and instead, bus usage is sacrificed much more. This is an outcome that government and urban planners may dislike. The finding suggests that at least for mid-dist trips, making car-sharing more competitive on its own is not sufficient; complementary policies are in absolute need for cutting down private car's demand.

Therefore, we develop another four scenarios (D, E1, E2 and F) which include policy options for raising private car's travel and parking costs. As we proposed earlier, adjusting car parking cost is possibly more flexible than adjusting car travel cost. Thus, 20% and 50% increase targets are applied to parking cost while 10% and 20% are applied to travel cost. These four scenarios are expected to join one of the intermediate scenarios B1 or B2 to create more effective and more practical policy packages. A and C are not any longer considered since one shows the limited effect on modal split changes and the other may be too radical in real practice. Eventually, B2 is preferred than B1 in both distances due to the effectiveness it shows on improving car-sharing's market share.

The combined scenarios can reveal broader insights. First of all, the increases in car-sharing's market share (compare to the baseline) now come more from the falls in private car usage than in bus usage. For example, in the radical scenario B2+F, bus shrinks 0.6% and car shrinks 1.9% in mid-dist trips while bus shrinks 1.2% and car shrinks 2.4% in long-dist trips. Another discovery is on the effectiveness of the two car-attributes in reality. In mid-dist, raising car travel cost is a more effective measure than raising parking cost in suppressing car usage as per

[14] The findings on car correspond to the cross elasticity values. The probability to choose car is much more elastic to the changes in car-sharing's attributes in the long-dist case (0.180 is much higher than the rest).

their direct elasticity values (Table 8). However, parking cost increase has higher policy flexibility than car travel cost increase (50% vs. 20%). Thus, in real practice, intervention can be radical with either of the two options given their equal effects on private car's market share in B2+E1 and B2+E2. As a contrast, in long-dist, a radical parking cost increase of 50% is more effective than a radical car travel cost increase of 20% (again, see B2+E1 and B2+E2) due to parking cost has both greater elasticity and higher policy flexibility than car travel cost.

To conclude, we summarize the key takeaways for policy making in bullet points:

▪Our elasticity analysis identifies that people are less easily to switch away from private car when trip distance increases (the direct elasticity values on car travel and parking costs are greater for mid-dist trips than for long-dist trips). Thus, policy measures on raising car travel cost and parking cost should be prioritized for shorter trips to avoid inefficient use of resources (though the threshold/criterion for shorter and longer trips warrants more research).

▪The above conclusion leads to two subsequent questions: if such policy measures are truly needed for shorter trips, and what the alternative solution could be to suppress private car demand for longer trips. Our policy impact analysis reveals the answers. In the mid-dist case, when car-sharing service is made more appealing, the increasing demand mainly comes from a shrinking demand for bus rather than for private car. Therefore, the policy measures on private car attributes are in absolute need and should be implemented alongside any car-sharing promotion policies. In the long-dist case, private car users are found much easier to switch to a better car-sharing service. Therefore, instead of the inelastic measures of raising the costs of using car, it is more effective to improve the attractiveness of car-sharing and make it as a practical substitute to private car.

▪The effectiveness of various car-sharing promotion policies differs across distances. In shorter trips, decreasing travel cost is more effective than travel time whereas in longer trips, decreasing travel time is more effective than travel cost. The finding fits well into microeconomic theory (Wardman, 1998; Axhausen et al., 2008; Shires and De Jong, 2009). Besides, any aggressive measures on access time reduction should be avoided especially when resources are constrained. It is rather preferred to reduce travel cost more aggressively in mid-dist case and travel time more aggressively in long-dist case.

▪Back to the shorter trip case where policy measures on private car attributes are needed, we recommend that it is up to the discretion of policy makers to prioritize car travel cost increase or parking cost increase when trade-off needs to be made given any practical constraints. The former is in itself more effective in suppressing private car demand while the latter is expected to have more rooms for policy intervention.

6. CONCLUSIONS

This paper studied the factors that could affect car-sharing choice and identified the effective policy options that could promote short-term car-sharing usage while suppressing private car demand. We conducted at first a mode choice analysis by using combined SP and RP survey data collected in the case study city, Taiyuan, China. Then, based on the choice model results, several informative indicators were derived such as willingness to pay for travel time savings, direct and cross point elasticity. Finally, we studied the modal substitution pattern in the SP environment to evaluate the effectiveness of different policy options. The results and relevant insights were generated separately for mid-dist trips (2km to 5km) and long-dist trips (more than 5km) throughout the paper.

Key findings are highlighted as follows. The willingness to pay for travel time savings for car-sharing is estimated as \$3.3/h in mid-dist trips and \$12.2/h in long-dist trips. Such a difference is in line with the existing findings which normally show the value increases with trip length (Wardman, 1998; Axhausen et al., 2008; Shires and De Jong, 2009). The values of cross elasticity are generally smaller than direct elasticity. This means the probabilities to choose car-sharing and private car are more sensitive to the level changes of their own attributes rather than the other's attributes. More critical insights are gained from the policy impact analysis. Raising the cost of car usage (e.g. via travel cost and parking cost) should be prioritized for shorter trips since car is more difficult to be substituted when trip distance increases. In fact, shorter trips also need such direct measures to help suppress the demand for private car while promoting the demand for car-sharing; otherwise the increasing demand for car-sharing would mainly come from bus users. On the contrary, longer trips would need an alternative and more effective solution to bring down private car usage and that is discovered as making car-sharing service more appealing so that it can serve as a practical substitute to private car. In addition, the effectiveness of car-sharing's travel time reduction is found to increase with trip length whereas the effectiveness of car-sharing's travel cost reduction decreases with trip length.

Overall, this research offered some direct insights regarding if more people choosing car-sharing "reduces the use of private vehicles or if, on the contrary, it reduces the number of public transport users" (Jorge and Correia, 2013). The results and the evidence derived from the policy impact analysis can be taken away as useful guidance to steer the demand for car-sharing in a short run.

Nevertheless, a short-term focus could also lead to an important limitation of this work. Ben-Akiva and Bierlaire (1999) argued that short-term travel decisions can be conditional on long-term travel decisions. As we mentioned earlier, Le Vine et al. (2014) also found the decisions of choosing car-sharing to conduct a daily trip can be a joint outcome of travellers' long-term and short-term behaviors. In other words, not only could car-sharing choice depend on surrounding tactical-level conditions (e.g. the various factors identified in this research), but the choice might also be affected by if an individual owns a car or holds a car-sharing membership, i.e. the long-term strategic choice. In this research, the mode choice observations come from an SP choice experiment, which focused on individuals' short-term travel behaviors. As for long-term mobility choices, most car-sharing services operated in China do not require subscription/membership commitment, which could make the membership effect on mode choice trivial; however, in an SP scenario, people may give a hypothetical car-sharing choice without fully taking into account the fact that if they own a car in real life, and hence yielding overly optimistic results on car-sharing demand (Ciari et al., 2016). Further research using SP based data to study car-sharing's modal substitution pattern should aim to limit such a bias by making survey participants aware of the effect of their long-term choice behaviors (e.g. car ownership) on short-term mode use decisions.

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CONFLICT OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest.

AUTHORS' CONTRIBUTION

W Li: Literature Search and Review, Data Collection and Analysis, Manuscript Writing

M Kamargianni: Content planning, Data Collection and Analysis, Manuscript Editing

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APPENDIX A: An example of a mid-dist scenario and a long-dist scenario as seen in the survey (translated from Chinese)

Mid-dist: Travel within 2-5km, to leisure, sunny day, 20°C, with excellent air quality

	Car share	**Car**	**Taxi**	**Bus**	**E-bike**	**Bike share**
	Travel 20 min	Travel 15 min	Travel 10 min	Travel 20 min	Ride 20 min	Ride 30 min
	Cost ￥8	Fuel ￥3	Cost ￥18	Ticket ￥1		Cost ￥0
		Hard to park car				
		Parking ￥5/h				
	Walk 15 min to station			Walk 10 min to station		Walk 2 min to station
				Every 5 min		
	With app		With app	Without app		With app
Your choice (please tick)						

Long-dist: Travel more than 5km, to work/education, rainy day, 30°C, with good air quality

	Car share	**Car**	**Taxi**	**Bus**	**E-bike**	**Bike share**
	Travel 25 min	Travel 20 min	Travel 30 min	Travel 30 min	Ride 20 min	Ride 60 min
	Cost ￥20	Fuel ￥5	Cost ￥25	Ticket ￥2		Cost ￥1.5
		Easy to park car				
		Parking ￥2/h				
	Walk 5 min to station			Walk 10 min to station		Walk 2 min to station
				Every 5 min		
	With app		Without app	With app		With app
Your choice (please tick)						

APPENDIX B: NL Results for Mid-dist Case and Long-dist Case

Mid-dist:

	SP data		SP & RP data	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{carshare}$ (SP)	- 1.91	- 8.38	- 1.68	- 7.18
α_{car} (SP)	- 0.63	- 2.28	- 0.52	- 1.98
α_{taxi} (SP)	- 2.48	- 7.66	- 2.38	- 7.46
α_{bus} (SP)	- 0.53	- 1.96	- 0.27	- 1.03
$\alpha_{bikeshare}$ (SP)	2.45	9.27	2.52	9.60
$\alpha_{cardriver}$ (RP)			2.29	4.86
$\alpha_{carpassenger}$ (RP)			- 0.89	- 3.10
α_{taxi} (RP)			0.19	0.72
α_{bus} (RP)			2.48	5.15
α_{ebike} (RP)			1.88	3.76
α_{bike} (RP)			0.37	0.90
Natural environmental conditions				
Air pollution-carshare (SP)	0.0094	9.38	0.0096	9.63
Air pollution-car (SP)	0.0033	3.47	0.0034	3.63
Air pollution-taxi (SP)	0.0035	2.72	0.0027	2.06
Air pollution-bus (SP)	0.0015	1.67*	0.0012	1.35*
Air pollution-bikeshare (SP)	- 0.0177	- 13.36	- 0.0175	- 13.21
Rain-ebike (SP & RP)	- 0.94	- 4.74	- 0.64	- 4.18
Temperature-taxi (SP)	- 0.01	- 2.16	- 0.01	- 2.14
Temperature-ebike (SP)	0.02	4.38	0.02	4.06
Trip and mode attributes				
Commute-carshare (SP)	- 0.62	- 3.94	- 0.66	- 4.32
Commute-taxi (SP & RP)	- 1.20	- 6.14	- 1.02	- 5.45
Commute-ebike (SP & RP)	0.50	4.64	0.42	4.31
Commute-bikeshare (SP & RP)	0.32	2.39	0.14	1.27*
Travel cost-carshare (SP)	- 0.03	- 2.69	- 0.03	- 2.76
Travel cost-car (SP & RP)	- 0.06	- 0.56*	- 0.19	- 2.47
Travel cost-taxi (SP & RP)	- 0.05	- 3.35	- 0.05	- 3.26
Travel cost-bus (SP & RP)	- 0.10	- 0.90*	- 0.08	- 0.82*
Travel cost-bikeshare (SP & RP)	- 0.38	- 3.72	- 0.46	- 4.70
Parking cost-car (SP)	- 0.06	- 4.14	- 0.06	- 3.86
Parking space-car (SP)	0.14	1.24*	0.04	0.36*
Travel time-carshare (SP)	- 0.01	- 1.49*	- 0.03	- 2.92

Travel time-car (SP & RP)	- 0.01	- 0.34*	- 0.01	- 0.24*
Travel time-taxi (SP & RP)	- 0.01	- 0.26*	- 0.03	- 1.88
Travel time-bus (SP & RP)	- 0.02	- 1.88	- 0.03	- 4.21
Travel time-ebike (SP & RP)	- 0.04	- 3.72	- 0.01	- 0.99*
Travel time-bikeshare (SP & RP)	- 0.15	- 11.51	- 0.14	- 11.38
Travel time-bike (RP)	-	-	- 0.01	- 0.17*
Waiting time-bus (SP)	- 0.03	- 4.02	- 0.03	- 3.84
Access time-carshare (SP)	- 0.04	- 2.78	- 0.04	- 2.69
Access time-bikeshare (SP)	- 0.25	- 12.03	- 0.24	- 11.74
App availability-carshare (SP)	0.18	2.10	0.18	2.18
App availability-taxi (SP)	0.32	2.26	0.40	2.88
App availability-bus (SP)	0.16	2.24	0.16	2.16
App availability-bikeshare (SP)	3.11	10.98	3.28	11.62
Systematic taste heterogeneity				
Air pollution * Male-bus (SP)	- 0.0022	- 5.77	- 0.0022	- 5.76
Air pollution * Lower age-taxi (SP)	0.0027	3.45	0.0025	3.20
Air pollution * Lower age-bus (SP)	0.0028	6.46	0.0028	6.66
Air pollution * Lower education-carshare (SP)	- 0.0034	- 4.67	- 0.0032	- 4.42
Air pollution * Lower education-taxi (SP)	- 0.0030	- 3.35	- 0.0017	- 1.92
Commute * Lower education-carshare (SP)	0.54	3.24	0.46	2.80
Commute * Lower education-taxi (SP & RP)	0.48	2.06	0.03	0.14*
Inter-alternative correlation				
$\mu_{selfdriven}$ (SP)	2.81	14.75#	2.80	17.53#
Scaling factor (RP)	-	-	0.76	4.27#
Number of observations	6848		11655	
Initial log-likelihood	- 10738.4		- 15408.3	
Final log-likelihood	- 9038.7		- 12705.8	
Likelihood ratio test	3399.3		5405.0	
Adjusted rho-bar squared	0.15		0.17	

Note: * parameter values not meeting the 90% significance level

t-test against base value of 1

Long-dist:

	SP data		SP & RP data	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{carshare}$ (SP)	- 2.61	- 5.32	- 1.79	- 6.32
α_{car} (SP)	- 1.22	- 3.01	0.10	0.58
α_{taxi} (SP)	- 2.26	- 5.33	- 0.50	- 2.67

α_{bus} (SP)	1.07	2.62	1.58	8.49
α_{ebike} (SP)	- 0.81	- 2.05	- 0.12	- 0.74
$\alpha_{cardriver}$ (RP)	-	-	- 0.23	- 7.33
$\alpha_{carpassenger}$ (RP)	-	-	- 0.32	- 7.62
α_{taxi} (RP)	-	-	- 0.21	- 6.35
α_{bus} (RP)	-	-	- 0.16	- 6.96
α_{ebike} (RP)	-	-	- 0.21	- 7.07
α_{bike} (RP)	-	-	- 0.17	- 5.74
Natural environmental conditions				
Air pollution-carshare (SP)	0.0088	14.49	0.0060	13.02
Air pollution-car (SP)	0.0062	13.17	0.0044	11.53
Air pollution-taxi (SP)	0.0050	13.28	0.0042	12.82
Air pollution-bikeshare (SP)	- 0.0217	- 6.58	- 0.0130	- 6.97
Rain-car (SP & RP)	0.39	3.67	0.07	4.58
Rain-taxi (SP & RP)	0.59	4.60	0.07	4.09
Rain-bus (SP & RP)	0.21	2.29	0.08	5.12
Rain-ebike (SP & RP)	- 0.14	- 1.23*	- 0.06	- 3.84
Rain-bikeshare (SP & RP)	- 0.54	- 2.56	- 0.06	- 4.09
Temperature-carshare (SP)	- 0.03	- 4.40	- 0.03	- 4.86
Temperature-taxi (SP)	- 0.04	- 7.60	- 0.03	- 6.50
Temperature-bus (SP)	- 0.04	- 11.04	- 0.02	- 8.07
Temperature-bikeshare (SP)	0.05	4.45	0.01	3.00
Trip and mode attributes				
Commute-carshare (SP)	1.34	8.85	0.99	8.87
Commute-taxi (SP & RP)	0.33	2.99	- 0.03	- 2.99
Commute-bus (SP & RP)	0.22	2.08	- 0.09	- 6.39
Commute-bikeshare (SP & RP)	- 2.33	- 5.47	- 0.07	- 6.37
Travel cost-carshare (SP)	- 0.04	- 4.61	- 0.04	- 5.97
Travel cost-car (SP & RP)	- 0.02	- 1.11*	- 0.01	- 7.30
Travel cost-taxi (SP & RP)	- 0.02	- 3.14	- 0.02	- 10.25
Travel cost-bus (SP & RP)	- 0.61	- 13.77	- 0.03	- 4.03
Travel cost-bikeshare (SP & RP)	- 0.78	- 5.04	- 0.04	- 0.59*
Parking cost-car (SP)	- 0.07	- 4.98	- 0.05	- 3.98
Parking space-car (SP)	0.27	3.14	0.09	1.44*
Travel time-carshare (SP)	- 0.07	- 7.52	- 0.04	- 6.16
Travel time-car (SP & RP)	- 0.03	- 2.87	- 0.01	- 5.88
Travel time-taxi (SP & RP)	- 0.02	- 2.07	- 0.02	- 9.69

Travel time-bus (SP & RP)	- 0.01	- 0.82*	- 0.01	- 5.61
Travel time-ebike (SP & RP)	- 0.02	- 6.54	- 0.01	- 5.72
Travel time-bikeshare (SP & RP)	- 0.04	- 6.19	- 0.01	- 7.17
Travel time-bike (RP)	-	-	- 0.01	- 4.25
Waiting time-bus (SP)	- 0.02	- 1.90	- 0.05	- 8.26
Access time-carshare (SP)	- 0.04	- 4.10	- 0.04	- 4.32
Access time-bus (SP)	- 0.16	- 15.42	- 0.10	- 11.95
Access time-bikeshare (SP)	- 0.09	- 2.89	- 0.04	- 1.51*
App availability-carshare (SP)	0.53	3.37	0.97	8.83
App availability-taxi (SP)	0.24	2.80	0.13	1.86
Systematic taste heterogeneity				
Air pollution * Male-bikeshare (SP)	0.0041	2.95	0.0030	2.72
Air pollution * Lower income-car (SP)	- 0.0017	- 5.34	- 0.0018	- 6.01
Air pollution * Lower education-car (SP)	- 0.0013	- 4.57	- 0.0008	- 2.98
Temperature * Male-carshare (SP)	- 0.01	- 2.99	- 0.01	- 2.70
Temperature * Male-bus (SP)	- 0.01	- 5.05	- 0.01	- 5.20
Temperature * Lower age-carshare (SP)	0.01	3.90	0.01	4.41
Temperature * Lower age-taxi (SP)	0.02	5.48	0.02	4.86
Commute * Lower income-bus (SP & RP)	0.24	2.88	0.08	6.22
Commute * Lower education-carshare (SP)	- 0.24	- 3.67	- 0.22	- 3.44
Inter-alternative correlation				
$\mu_{sharingeconomy}$ (SP)	2.71	7.58#	2.49	8.13#
Scaling factor (RP)	-	-	1.29	8.10#
Number of observations	11925		21824	
Initial log-likelihood	- 18938.3		- 35361.5	
Final log-likelihood	- 15438.8		- 27555.7	
Likelihood ratio test	6999.2		15611.6	
Adjusted rho-bar squared	0.18		0.22	

Note: * parameter values not meeting the 90% significance level
t-test against base value of 1