Examining the impact of car-sharing on private vehicle ownership

Fan Zhou[a,e], Zuduo Zheng[b,*], Jake Whitehead[b,g], Robert K. Perrons[c,f], Simon Washington[b], Lionel Page[d]

[a] *Zhijiang Institute for Statistics and Big Data, Zhejiang Gongshang University, China*
[b] *School of Civil Engineering, University of Queensland, Australia*
[c] *Queensland University of Technology, Brisbane, Australia*
[d] *Economics Discipline Group, University of Technology Sydney, Australia*
[e] *International Business School, Zhejiang Gongshang University, China*
[f] *Centre for Strategy and Performance, University of Cambridge, United Kingdom*
[g] *The UQ Dow Centre for Sustainable Engineering Innovation*

Abstract

Car-sharing has experienced a significant boom in recent years, with estimates suggesting that car-sharing programs are now operating in over 30 countries worldwide, serving around five million users. The potential to reduce individual vehicle ownership rates is frequently cited as a motive for promoting car-sharing. While some previous studies have argued that customers are indeed willing to reduce the total number of vehicles owned after becoming car-sharing members, the reliability of these findings is tenuous given that many are based on self-selected samples of car-sharing users, resulting in biased estimates. In theory, the availability of car-sharing programs could have limited effect on the general public's car ownership decisions—or at least have no effect on a large portion of travelers. Whether or not traveler decision processes are significantly influenced by specific attributes of different car-sharing options (e.g., access time, vehicle size, fuel type, etc.) remains an unanswered question, as there are limited quantitative studies on this issue. To contribute to filling this research gap, this paper discusses the findings of a study of 1,500 private households across major Australian cities. A nested logit model is used to investigate the impacts of car-sharing on respondents' household vehicle ownership decisions. In contrast to the results of some previous studies, we find that the stated availability of car-sharing appears to have minimal impact on respondents' decision to own a vehicle or not, leading to important policy implications. We agree with prior investigations that car-sharing could potentially reduce private car ownership. However, because this study finds limited impact of the availability of car-sharing on vehicle ownership, and because the majority of respondents did not self-identify as car-sharing users, education and awareness campaigns could be important factors in improving the general public's preferences towards car-sharing and fully realizing car-sharing's benefits to society.

Keywords: car-sharing, vehicle ownership, shared economy, shared autonomous vehicles (SAVs)

1. Introduction

In recent years, shared mobility schemes, particularly car-sharing, have received significant interest from transport researchers, planners, and policymakers due to the challenges that communities face from the continued growth of vehicle ownership and usage, along with the associated consequences such as increased traffic congestion, parking congestion, and air pollution (greenhouse and particulate emissions). Car-sharing programs have the potential to reduce both personal vehicle usage and rates of ownership, as well as to encourage individuals to use alternative modes of transport (e.g., public transport, cycling, walking, etc.) more frequently (Martin and Shaheen, 2011).

The ability to share the fixed costs of vehicle ownership represents the principal economic benefit of car-sharing (Duncan, 2011). Through car-sharing programs, individuals gain the benefits equivalent (or close to equivalent) to owning a private vehicle, without the burden of complete ownership (e.g., insurance, maintenance, etc.). Particularly for those low-income households that cannot afford to own a private vehicle, they can benefit from increased mobility in highly automobile-dependent societies through the availability of car-sharing (Litman, 2000). The group that could benefit the most from car-sharing can be easily quantified using census data. For example, according to the Australian Bureau of Statistics (ABS, 2011), 8.4% of households in Australia did not own a private vehicle in 2011. In the U.S., 10% of households had no access to private vehicles as of 2000 (Duncan, 2011). By implementing car-sharing services, non-car owners could benefit from increased options and/or flexibility. More specifically, these consumers will benefit from easy access to vehicles when they need them, without the financial burden of vehicle ownership, which is likely to increase their utility.

In addition to carless households, the financial benefits of car-sharing also influence car owners who only drive occasionally. For instance, as shown by Litman (2000) and Prettenthaler and Steininger (1999), vehicle owners would be better off switching to car-sharing from private cars if they drive less than 10,000 km (15% of vehicles) and 15,000 km (69% of households) per year in the U.S. and Austria, respectively.

One of the main streams in car-sharing research is to study its impacts on personal vehicle ownership. Although considerable effort has been made to measure the effects of car-sharing (Martin and Shaheen, 2011; Martin et al., 2010; Huwer, 2004; Zhou et al., 2017), there are several challenges. Firstly, prior studies have usually been drawn on data from existing car-sharing organizations or operators (i.e., revealed preference data). Thus all respondents were already car-sharing members, and most of them do not own a car (Martin et al., 2010). Self-selection bias could arise in this situation, more specifically, the early adopters of car-sharing who self-selected themselves into the group were also found to be more environmentally conscious and willing to commit to more sustainable behaviors (Costain et al., 2012). Therefore, the prior findings may be over-optimistic about the impacts of car-sharing on household vehicle ownership, and the availability of car-sharing programs could have only minimal or even no effect on vehicle ownership of general public.

*Corresponding author: Zuduo Zheng
Email address: zuduo.zheng@uq.edu.au (Zuduo Zheng)

Secondly, there is a lack of quantitative studies on the impacts of car-sharing on vehicle ownership. While prior vehicle ownership studies rarely incorporated car-sharing, the car-sharing focused research is insufficient due to the reason listed in the first point (i.e., sample selection biases). To expand the scope to be representative of the general public, stated preference analysis could be implemented, due to the low market penetration of car-sharing.

Thirdly, there is a general lack of studies on the impacts of the shared autonomous vehicles (SAVs) on vehicle ownership from the perspective of consumers. It is argued that the advent of SAVs has the potential to reduce the level of car ownership, for example, (Schoettle and Sivak, 2015) state that SAVs could reduce up to 43% of vehicle ownership. However, the full benefits could only be achieved if consumers are willing to give up their private vehicles for SAVs.

The primary objective of this paper is to quantitatively investigate whether conventional car-sharing programs and SAVs have significant impacts on people's vehicle ownership decisions, and whether previous studies have over-estimated the potential impact of car-sharing programs. Towards this end, a national online survey was developed and administrated cross major Australian cities between July and August of 2016. The respondents considered were a sample of the general public rather than only car-sharing members. A nested logit (NL) model is employed to analyze the data.

The next section provides a review of the literature. Section 3 presents the methodological design of this study including the survey plan, data collection, and the model construction. Sections 4 and 5 describe the descriptive analysis and the choice modeling results, respectively. Finally, Section 6 concludes by summarizing and discussing the main findings.

2. Literature review

Households' decisions on vehicle ownership have been extensively studied in the literature. Mainstreams of household vehicle ownership models include vehicle purchase (VP), vehicle holding (VH), and vehicle transaction (VT) models (de Franca Doria et al., 2009; Anowar et al., 2014). The VP models describe the likelihood that a household will decide to purchase a new vehicle with given attributes (e.g., price, make, performance, environmental characteristics, vehicle attributes, etc.) or predict the choice of the most recent purchased vehicles associated with the vehicle attributes. These models have successfully quantified consumers' preferences toward private vehicles, which in turn produces market share estimates (Paleti et al., 2013b; Lave and Train, 1979; Mannering and Mahmassani, 1985; Choo and Mokhtarian, 2004; Brownstone et al., 2000; Hensher and Greene, 2001; Sierzchula et al., 2014; Rezvani et al., 2015; Gallagher and Muehlegger, 2011). Moreover, the VH models explore the probability that a household with given characteristics will own a particular number of vehicles at some point of time. The households' vehicle holding levels are found to be correlated with residential location, income, household size, and location (Bhat and Pulugurta, 1998; Hanly and Dargay, 2000; Baldwin Hess and Ong, 2002; Whelan, 2007; Paleti et al., 2013a). In addition, the VT models concern the change of the total number of vehicles owned by households, such as replacement and disposal decisions. For example, a nine year records of household vehicle holding data was analysed by Mohammadian and Miller

(2003), Mohammadian and Rashidi (2007), and Rashidi and Mohammadian (2016) to study the transaction timing of consumers in Toronto area, the authors argue that the increased number of licensed drivers, member with higher education, employed workers is likely to trigger vehicle acquisition but a decrease in family members is likely to lead to vehicle disposal. These models are used to investigate the impacts of life-changes (e.g., increased/decreased adults or children) on vehicle transaction or to forecast the change of ownership and the duration of the transactions (Yamamoto, 2008; Gilbert, 1992; de Franca Doria et al., 2009). However, car-sharing has rarely been considered in existing vehicle ownership studies.

Studies that focus on car-sharing's impacts on vehicle ownership usually rely on real-world data from car-sharing operators. More specifically, based on investigations of car-sharing users only and by comparing the total number of households' private vehicles before and after joining car-sharing programs. Prior studies argue that car-sharing effectively reduced respondents' private vehicle ownership. For instance, Martin and Shaheen (2011) and Martin et al. (2010) surveyed car-sharing members in the U.S., asking about changes in private car ownership after joining car-sharing programs. The authors observe that the total vehicles owned by the 6,281 households surveyed decreased from 2,968 to 1,507. In the European context, it was also observed that car-sharing leads to a decrease in vehicle ownership, as summarized in Katzev (2003), a decline of 44%, 60%, and 25% are reported by car-sharing members in Netherlands, Switzerland, and Canada respectively. However, these findings only reflect the behavior of early adopters and are not representative of the general public, due to sample selection bias or self-selection bias (Heckman, 1977; Rodier and Shaheen, 2003; Willis and Rosen, 1979). Car-sharing users that self-selected themselves into the car-sharing user group were also found to be more educated, wealthier, environmentally conscious, and innovative individuals who are willing to commit to social activities and try new products (Costain et al., 2012; Burkhardt and Millard-Ball, 2006; Rodier and Shaheen, 2003; Shaheen and Rodier, 2005). Therefore, focusing on car-sharing users, prior studies expected too much of the impacts of car-sharing on vehicle ownership.

As discussed previously, the majority of the studies focused on car-sharing are descriptive. Kim et al. (2017) is one of the very limited studies that quantitatively investigated car-sharing's impacts on vehicle ownership. The authors considered vehicle purchasing decisions with car-sharing by adding 'Buy 2nd car' as an alternative to 'Join car-sharing.' However, the authors ignored the selling decision as an alternative, and it is therefore doubtful whether 'Buy 2nd car' and 'Join car-sharing' are appropriate alternatives because these two options are not mutually exclusive. More specifically, car-sharing is complementary to our current transport systems, for instance, consumers can use car-sharing for shopping but drive their private car for other trips. Buying the second car does not mean that a consumer will not use car-sharing and similarly join car-sharing does not strictly prohibit a consumer from buying a second car. Therefore, our understanding of car-sharing's impacts could be advanced by implementing a quantitative study that explains the effects of each car-sharing related attribute on respondents' vehicle ownership decisions.

Furthermore, regarding SAVs, one of the early assessments of SAVs is made by Fagnant and Kockelman (2018). The authors considered the potential impacts of SAVs, including reduced crashes and accidents, thus fewer associated injuries, less congestion, and the reduced need for parking, etc. Thus, the benefits of each SAV per year is estimated to be about USD \$2,960 (10% market share of SAV assumed) and up to \$3,900 (90% market share of SAV assumed) in the American context. Schoettle and Sivak (2015) claim that multiple residents can be served by one SAV and they estimated that the SAVs could reduce vehicle ownership by up to 43% and increase the usage of each remaining vehicle by up to 75%. This, in turn, cuts the travel costs, reduces vehicle ownership cost and parking cost, and consequently leads to a reduction in parking spaces needed (Burns, 2013; Fagnant and Kockelman, 2015; Schonberger and Gutmann, 2013). Several studies (i.e., Chen et al. 2016; Fagnant and Kockelman 2014; Zhang et al. 2015) agree that SAVs lead to a decrease in vehicle ownership, in the meantime, maintaining an equal level of mobility supply. However, there is a lack of studies on the impacts of the SAVs on vehicle ownership from the consumers' perspective. It is argued that the advent of SAVs has the potential to reduce the level of car ownership, however, the full benefits of SAVs can only be achieved if consumers are willing to give up their private vehicles and adopt these new services.

3. Methodology

3.1. Data collection

This study is based on data collected in a large-scale survey conducted in late 2016. The online survey was implemented across major Australian cities–including Sydney, Melbourne, Brisbane, and Adelaide—which was completed by 1,433 respondents. Four responses (repeated SP experiment) were collected from each of the respondents, resulting in 5,732 observed scenarios. It is known that asking too many questions could impose a significant cognitive burden to respondents, which in turn reduce both the response rate and reliability (Hensher et al., 2015). After two rounds of pilot test and discussion within the research team and external experts, we believe the workload of a survey contains four SP experiment, which requires 20 - 25 minutes on average to complete, is reasonable. Great efforts have been made to maximize the coverage across both the combinations of alternatives (i.e., scenarios) and to maximize the variability of the alternative attributes, to force trade-offs. The objective was to collect 1500 responses, we should have approximately 11-12 completed responses per choice task if each respondent was presented with four unique choice tasks (i.e., $1500 \times 4/512 = 11.72$, 512 unique choice tasks were generated). Standard practice usually mandates around 20 completes per choice task, but given the complexity of the experiment design, we believe 11 completes per choice task should suffice for this study. The survey collected both revealed preferences (RP) and stated preferences (SP) on vehicle buy/sell decisions. RP information is useful in gaining an understanding of consumers' current choices (or choices that have been made by the consumers in the past), and what factors are likely to influence their current choices; SP information, on the other hand, are used to obtain consumers' reactions to choices presented to them about the future (e.g., self-driving vehicles). As suggested by Zheng et al. (2016), SP is popular due to the relatively low associated time and financial cost, and it is particularly useful when new attributes and alternatives are involved—like, for example, the self-driving capability and SAVs included in this study.

Specifically, the survey consisted of four main parts. In the first part, household information, and each household member's travel and activity patterns were collected. The second part obtains information regarding vehicles (e.g., car and two-wheelers) currently owned by respondents. The third part of the survey featured a stated choice experiment (described in detail in Section 3.3). The last part of the survey collected demographic and household background information of the respondents.

A video clip was provided at the beginning of the SP experiment stage (the third part) to give essential and objective information on the new technologies (e.g., self-driving) and new mobility mode (e.g., car-sharing) to familiarize respondents with the terms before they were asked to make decisions on future vehicle choices. Respondents were required to watch the full video before proceeding to the SP experiment. The video was important in improving respondents' understanding of the new technology and novel mobility options, including car-sharing, given it has been shown that the awareness of car-sharing is usually low. For instance, a car-sharing survey conducted in Germany in 2002 showed that only 15% of the respondents could describe what car-sharing was or name or refer to a car-sharing organization (Loose et al., 2006). Thus, providing this video introduction helped to improve the quality of the survey responses. Note that precaution was exercised to ensure only factual information was provided to respondents to avoid introducing any potential bias from the research team. Fig. 1a to Fig. 1c present a series of screenshots of the video[1].

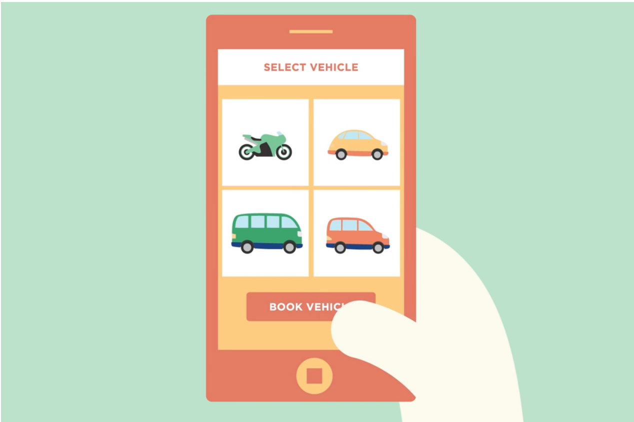


Figure 1a: Video screenshot of booking a shared car

Prior to launching the main survey, two pilots and a focus group were conducted, and some questions in the final survey were modified according to comments and feedback received. The final survey was conducted between 12 July and 15 August 2016. The final survey was implemented across major Australian cities, which includes Melbourne, Sydney, Brisbane, etc. To ensure the representativeness of the dataset, gender and age cohorts were sampled to achieve consistency with the latest population census from the Australian Bureau of Statistics (ABS, 2016).

[1]The full video is available at https://youtu.be/8sD0ymSj4j0. A company called Explanimate! (www.explanimate.com.au) was hired to convert the written script into an online animation.

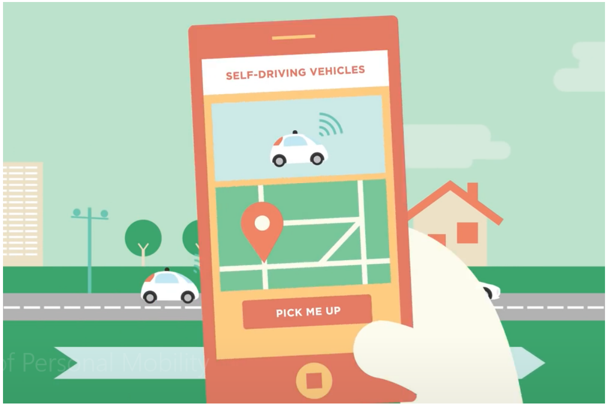


Figure 1b: Video screenshot of booking a shared self-driving car

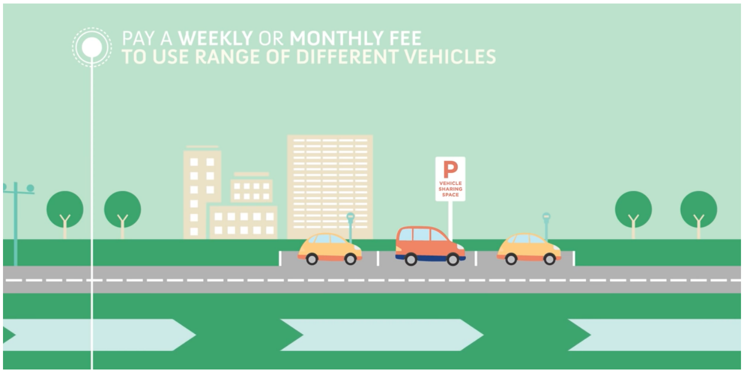


Figure 1c: Video screenshot of car-sharing service

In total, 2,015 respondents started the survey, and 1,433 of them completed it. The demographic details of the respondents are summarized in Table 1. As seen in this table, the gender-split is reasonably even between males and females. The majority of the decision-makers were between 25 and 54, which accounted for 68.8% of the respondents. Besides, most of them had a higher education degree (57.7%), which represented a relatively highly educated sample. The proportion of well-educated respondents was relatively high because only adults were included in this survey. Most of the respondents came from the capital cities in Australia including 33.6% from Sydney, 26.53% from Melbourne, 19.47% from Brisbane, 11.67% from Perth, and the rest 8.78% of respondents came from other cities. The sample is reasonably representative of the national population in relation to gender, age, and education distributions.

3.2. Data cleaning

As mentioned previously, the total number of scenarios presented was 5,732. The choice scenarios in this study were personalized to increase the realism of the SP experiment (and in turn, the reliability of the SP responses). The maximum options of hypothetical vehicles that could be presented to respondents were two, thus the new vehicle alternative(s) could be zero, one, or two. Additionally, the number of current vehicles were subject to respondents'

Table 1 Respondents profile

Gender	**Frequency**	**Breakdown**	**ABS (2016)**
Male	745	51.99%	49.3%
Female	678	47.31%	50.7%
Other	4	0.28%	-
Not answer	6	0.42%	-
Age			
Under 18	6	0.42%	24.8%
18-24	162	11.30%	6.7%
25-34	332	23.17%	14.4%
25-44	356	24.84%	13.5%
45-54	299	20.87%	13.3%
55-64	251	17.52%	11.8%
65-74	26	1.81%	8.9%
75 or older	1	0.07%	6.9%
Education			
Postgraduate	254	17.73%	-
Graduate	170	11.86%	-
Bachelor	403	28.12%	22%(Bachelor and above)
Diploma	198	13.82%	8.9%
Certificate	185	12.91%	15.8%
None	223	15.56%	-
City			
Sydney	476	33.22%	-
Melbourne	381	26.59%	-
Brisbane	282	19.68%	-
Perth	169	11.79%	-
Other cities	125	8.72%	-
Total	1433	100%	-

actual vehicle holding reported, and the maximum number of vehicles recorded was five. As shown in Table 2, in only 1.9% (109) of the experiment, respondents stated they would like to sell more than two vehicles. In order to control the complexity of the model, these 109 observations were removed, leaving an updated sample size of 5,623.

Furthermore, as shown in Table 3, in only 2.93% (or 165) of the experiment, respondents stated they would like to buy two hypothetical vehicles. Similarly, to control the complexity of the model, these 165 observations were eliminated and resulted in a sample size of 5,458. Another 89 observations were removed because neither current vehicles nor hypothetical vehicles were available in these cases, that is, those respondents do not own private vehicles, and in the experiment, future vehicle option was not provided to them by design. Thus, the final sample size used in the analysis was 5,369.

In the final sample, the maximum number of current vehicles and future vehicles are restricted at two and one, respectively. Therefore, respondents could decide to sell maximum

Table 2 Number of vehicles respondents stated to sell

Car sold	Frequency	Percentage	Cumulative
0	3529	61.57%	61.57%
1	1630	28.44%	90.00%
2	464	8.0%	98.10%
3	87	1.52%	99.62%
4	20	0.35%	99.97%
5	2	0.03%	100%
Total	5732	100%	100%

two current vehicles (i.e., zero, one or two) and/or buy at most one hypothetical vehicle.

Table 3 Number of vehicle respondents stated to buy

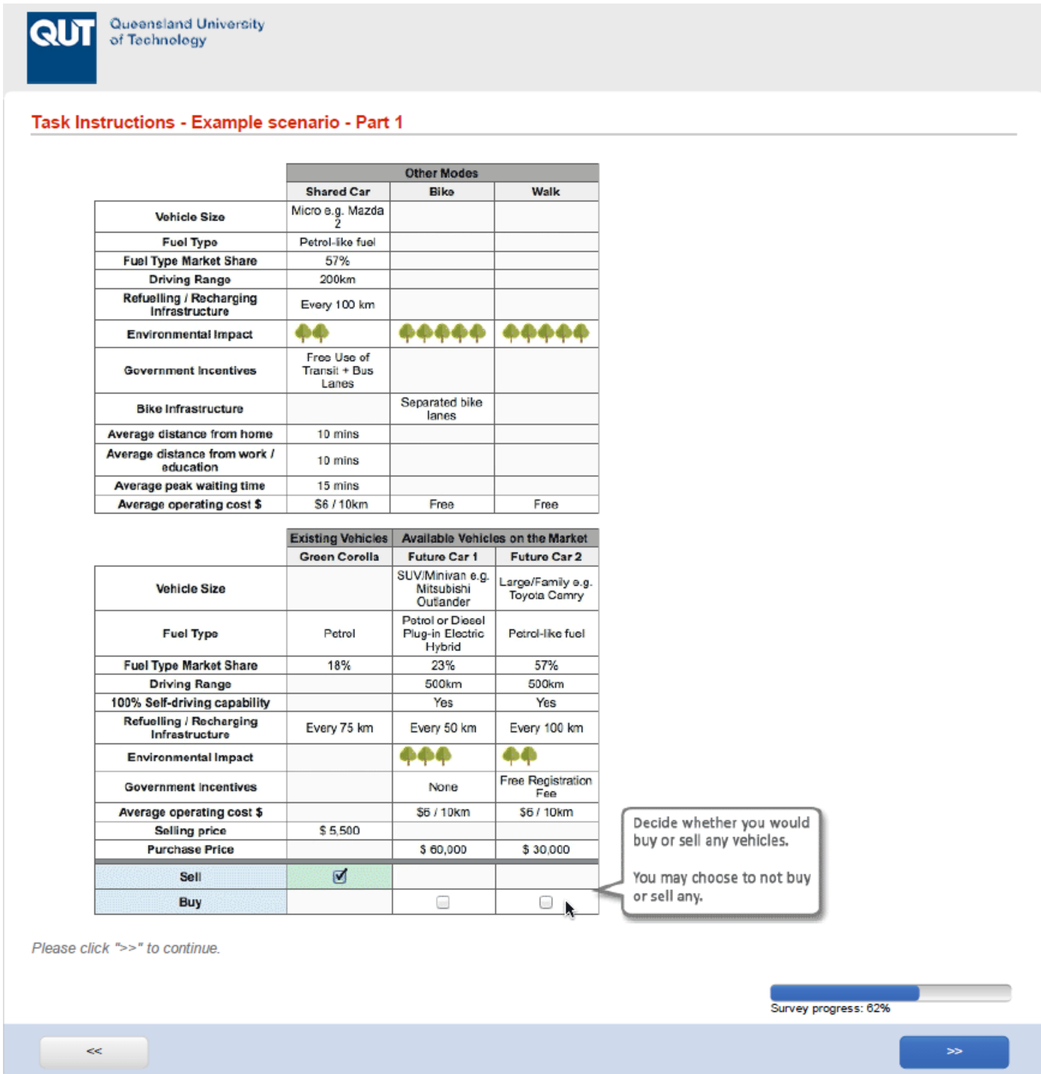
Car bought	Frequency	Percentage	Cumulative
0	4174	74.23%	74.23%
1	1284	22.83%	97.07%
2	165	2.93%	100%
Total	5623	100%	100%

3.3. Stated preference experiment

The SP experiment aimed to investigate whether the availability of car-sharing affected households' car ownership decisions. After watching the information video, respondents are required to answer a series of questions regarding their decisions on vehicle acquisition and/or disposal in four distinct scenarios. An example of the vehicle ownership choice SP experiment is demonstrated in Fig. 2. In this scenario, the respondents had one existing vehicle, which is a petrol-powered Green Corolla with an estimated current value of AU$5,500. The respondent is also presented with two future vehicles (i.e., vehicles hypothetically available on the market). Therefore, three alternatives in total are provided in this experiment. One of the future cars is a plug-in hybrid electric vehicle, and another is a conventional vehicle. Both the future cars are fully self-driving with the same operating cost (i.e., $6 per 10 km) and driving range (i.e., 500 km). However, the plug-in hybrid electric car is more expensive but also more environmentally friendly than the petrol-powered car.

In addition to the private car alternatives, three other transport modes, which includes car-sharing, bike and walk, are also included in this the experiment along with their attributes; for example, the shared car in this example (see Fig. 2) is a very small conventional vehicle with no automatic features. Also, attributes such as access distance, waiting time, cost, etc. are included. To avoid the mutually non-exclusive issue, this kind of information (i.e., other modes) existed, by design, only to remind respondents of the availability and associated features of these modes, rather than treating them as alternatives. This is also an attempt to mimic the real world, where people are aware of alternative mobility modes and these alternatives are compatible with the travel modes they owned privately.

Due to the complexity of the SP tasks, a tutorial-style instruction on how to respond to vehicle choice experiment is provided. As shown in Fig. 2, animated instructions with word descriptions were provided to guide respondents to complete the experiment step-by-step. Respondents are required to go through the example SP experiment before allowed to start doing the formal experiment.



	Other Modes		
	Shared Car	Bike	Walk
Vehicle Size	Micro e.g. Mazda 2		
Fuel Type	Petrol-like fuel		
Fuel Type Market Share	57%		
Driving Range	200km		
Refuelling / Recharging Infrastructure	Every 100 km		
Environmental Impact			
Government Incentives	Free Use of Transit + Bus Lanes		
Bike Infrastructure		Separated bike lanes	
Average distance from home	10 mins		
Average distance from work / education	10 mins		
Average peak waiting time	15 mins		
Average operating cost $	$6 / 10km	Free	Free

	Existing Vehicles	Available Vehicles on the Market	
	Green Corolla	Future Car 1	Future Car 2
Vehicle Size		SUV/Minivan e.g. Mitsubishi Outlander	Large/Family e.g. Toyota Camry
Fuel Type	Petrol	Petrol or Diesel Plug-in Electric Hybrid	Petrol-like fuel
Fuel Type Market Share	18%	23%	57%
Driving Range		500km	500km
100% Self-driving capability		Yes	Yes
Refuelling / Recharging Infrastructure	Every 75 km	Every 50 km	Every 100 km
Environmental Impact			
Government Incentives		None	Free Registration Fee
Average operating cost $		$6 / 10km	$6 / 10km
Selling price	$ 5,500		
Purchase Price		$ 60,000	$ 30,000
Sell	☑		
Buy		☐	☐

Figure 2: Sample screenshot of the stated preference experiment of car ownership choices

The level of the alternative-specific attributes is carefully designed to ensure each hypothetical scenario is both efficient and realistic. To improve the quality (or realism) of the SP experiment, whenever the real data are available (e.g., peak waiting time), the attributes' levels are pivoted from the revealed data by plus and minus a certain percentage (e.g., +/- 50%). When the real data are unavailable (e.g., the purchase price of a hypothetical vehicle), levels are pivoted from comparable real data (e.g., the price of the current vehicle). The variations across different levels are sufficiently large in order to fully capture all potential responses from respondents.

The selected attributes and associated levels are summarized in Table 4. As shown in this table, the price (or value) of current vehicles are defined by respondents, and the price for future vehicles ranged from AUD 20,000 to 60,000 in increments of AUD 10,000 (five levels). The average refuel distance also had five levels, ranging from 15 km to 100 km for both existing cars and hypothetical cars. Environmental impact is not applicable to respondents' existing cars, but there are four levels for the future vehicle. Level one denotes the least environmentally friendly cars, whereas level four indicates the most environmentally friendly options. Attributes such as self-driving capability are not applicable to current vehicles. The vehicle size attribute has four levels classified by the interior capacity of the vehicles, including micro vehicles (e.g., Mazda 2), compact vehicle (e.g., Ford Focus), Large vehicle (e.g., Toyota Camry), and SUV (e.g., Mitsubishi Outlander). The names will stick with the vehicle size, for example, respondents who encountered micro vehicle alternative will always see "micro e.g., Mazda 2". We provided a real-world example for each vehicle size to avoid potential misunderstanding; otherwise, people might have a different interpretation of the vehicle size.

Regarding car-sharing related attributes, "Car-sharing option" is an indicator variable that takes value one if car-sharing is presented to a respondent in the SP experiment as an option and zeroes otherwise (recall that the choice sets were personalized). Fig. 2 provides an example of the scenarios where car-sharing is presented to some respondents as an option. Also, a range of associated car-sharing attributes was provided to respondents if the car-sharing option was available. The "car-sharing driving range" has five levels ranged from 100 km to 500 km. "car-sharing micro-car", "car-sharing electric car" and "car-sharing self-driving capability" are all indicator variables that take value one, if the shared car is a micro-car (e.g., Mazda 2), electric car, or autonomous, otherwise zero. The average waiting time for car-sharing service is a continuous variable ranging from 3 min to 38 min.

In addition, commute distance could be an important explanatory variable. On the other hand, however, it would be difficult for the respondents to estimate their commute distance if we require them to self-report it. Moreover, if we provide an attribute of commute distance with several levels in the experiments, some values could be unreal or irrelevant to some respondents. For example, some people may use vehicles only for other purposes like shopping, education, recreation, etc. Instead, some other variables such as 'average operating cost', 'average distance from home', and 'average distance from work' probably could be viewed as a proxy of the distance and time respondents travel, as in order to calculate their total cost, respondents might need to (explicitly or implicitly) recall the total distance they traveled.

The last three attributes in Table 4 are control variables. "Bought two-wheeler" and "Sold two-wheeler" indicate that a respondent also decided to change their two-wheeler ownership in an experiment. "Household size$\geq$3" is a binary variable which takes the value of one if a household had three or more members, and zeroes otherwise.

Table 4 Selected attributes and their levels

Attribute	**Current Vehicle (CV)**	**Future Vehicle (FV)**
Price	Defined by respondents	20k; 30k; 40k; 50k; 60k
Average refuel distance	15km; 25km; 50km; 75km; 100km	15km; 25km; 50km; 75km; 100km
Environmental impact	–*	1, 2, 3, 4#
Fuel type	–	Petrol; Petrol-like; Hybrid; Electric
Self-driving capability	–	Yes=1; No=0
Operating cost	–	$4, $5, $6, $7, $8 per 10km
Petrol powered vehicle	–	Yes=1; No=0
Policy: free registration fee	–	Yes=1; No=0
Policy: free EV public charging	–	Yes=1; No=0
Policy: $5000 tax rebate	–	Yes=1; No=0
Policy: 50% toll road discount	–	Yes=1; No=0
Policy: free use of transit + bus lanes	–	Yes=1; No=0
Vehicle size (interior capability)	Micro 1, Compact 2, Large 3, SUV 4	
Fuel type market share	2% - 80%	
Car sharing option	Yes=1; No=0	
Car sharing access distance from home	Yes=1; No=0	
Car sharing access distance from work	Yes=1; No=0	
Car sharing average peak waiting	3min to 38min	
Car sharing driving range	100km; 200km; 300km; 400km;500km	
Car sharing policy: free use of transit + bus lanes	Yes=1; No=0	
Car sharing fuel type	Petrol; Petrol-like; Hybrid; Electric	
Car sharing self-driving capability	Yes=1; No=0	
Car sharing environmental impact	1, 2, 3, 4	
Household size≥3	Yes=1; No=0	
Bought two-wheeler	Yes=1; No=0	
Sold two-wheeler	Yes=1; No=0	

*: "–" means that this attribute is not applicable.

#: 1 denotes least environmental friendliness; 4 denotes most environmental friendliness.

Ngene[2] (ChoiceMetrics, 2014) was used to design the SP scenarios, a balance fractional orthogonal design was used to construct 32 unique market structure scenarios. This is known as the availability design (as it determines what alternatives are available under a given scenario). Two properties were hold in this step: balance and orthogonality, meaning that each level corresponding to an alternative appears an equal number of times, and the availability of each alternative is independent of the availability of any other alternative. The attributes and their levels were kept balanced and independent based on the ideas of 'utility balance'(Huber and Zwerina, 1996). Utility balance refers to choice scenarios in which respondents have similar utilities for each of the available alternatives, and are therefore faced with a difficult choice. Difficult choices force respondents to make trade-offs that they would not have had to make in the case of easy choice tasks where one alternative is clearly preferred. Consequently, difficult choice tasks implicitly reveal more about the underlying structure to the respondent's preferences.

[2] "Ngene is software for generating experimental designs that are used in stated choice experiment for the purpose of estimating choice models, particularly of the logit type", Ngene 1.1.1 User Manual & Reference Guide.

3.4. Car-sharing availability model and Car-sharing effect model

Two models were estimated to investigate the impacts of car-sharing on households' vehicle ownership: (1) Car-sharing availability model, and (2) Car-sharing effects model. The outcome variables (alternatives) are the same for the two models. The car-sharing availability model (i.e., first model) is based on the full sample (i.e., N=5,369) to investigate the impacts of the car-sharing option on car ownership. In order to answer this question, a straightforward and effective way is to include a single variable related to car-sharing in the model: an indicator for car-sharing availability. Principal Component Analysis (PCA) was employed to construct the indicator, it also ensures car-sharing attributes are incorporated as much as possible. The PCA generated indicator could be used in the model to represents the car-sharing programs with different combinations of attributes levels. More specifically, range, environmental effect, refuel distance, cost, access distance from home, access distance from work, average waiting time, car-sharing market share are considered in PCA. As shown in Table 5, the results suggest that the first component with an eigenvalue of 5.777 explains 72.2% of the total variance, which is very close to the 75% threshold (Kaiser, 1960; Morrison, 1990). To control the complexity of the model, we decided to only include the first component.

Table 5 PCA of car-sharing attributes

	Eigenvalue	Cumulative
Component 1	5.777	.722
Component 2	.542	.79
Component 3	.424	.843
Component 4	.349	.886
Component 5	.323	.927
Component 6	.258	.959
Component 7	.219	.986
Component 8	.109	1

The car-sharing effect model (i.e., second model) focuses on the 2,707 scenarios with car-sharing option (recall that among the 5,369 SP experiment, the car-sharing option is presented to respondents in only 2,707 of the scenarios). This model tested whether the car-sharing related attributes (e.g., driving range, self-driving capability, wait time, etc.) affected respondents' decisions on private vehicles.

Instead of using two models, an alternative approach is to combine the two models by incorporating the car-sharing attributes into the first model mentioned above (car-sharing availability model), more specifically, a series of interactions between the car-sharing option dummy and the attributes could be included in this model. Compared to model 2 proposed above, this combined model makes use of the full data and the effect of car-sharing option is differentiated according to each attribute, however, this is incapable of answering the research question that whether the availability of car-sharing has impacts on private vehicle ownership directly. This question has seldom been quantitatively investigated in the literature (recall that previous studies usually compare the household car holdings before and after joining car-sharing programs). Therefore, we believe that more information could be extracted from the data with two separate models. Nevertheless, the results of this alternative model are presented in Appendix A.

A nested logit (NL) model is employed to model the data collected via the vehicle ownership SP experiment. By allowing the random components to be correlated within each subset (or "nest") of alternatives, the NL model (Ben-Akiva, 1973) relaxes the restrictive independence of irrelevant alternatives (IIA) assumption of multinomial logit model (MNL). The NL model requires the alternatives to be constructed into a decision tree, in other words, the alternatives need to be split into levels (or groups). NL is convenient when the choice alternatives are multidimensional in nature, for instance, vehicle type and mode choices.

3.5. Decision tree structure

The maximum number of cars respondents can decide to sell or buy is two and one in the SP experiment, respectively. Therefore, there are in total six alternatives as shown in Table 6: D2 - selling two current vehicles while buying no future vehicle, D1 - selling one current vehicle but buying no future vehicle, RPD1-selling two current vehicles while buying one future vehicle, RP - selling one current vehicle while buying one future vehicle, SQ (status quo)-doing nothing, and BUY - buying one future car without selling any current vehicles. Each alternative's frequency in the survey and its consequence on the overall change of the vehicle ownership are also provided in Table 6.

Table 6 Alternatives of the vehicle ownership model

Alternative	**Current car**	**Future car**	**Overall change**	**Frequency**	**Percentage**
D2	Sell 2	No change	Decrease 2	141	2.58%
D1	Sell 1	No change	Decrease 1	896	16.42%
RPD1	Sell 2	Buy 1	Decrease 1	157	2.88%
RP	Sell 1	Buy 1	No change	731	13.39%
SQ	No change	No change	No change	3137	57.48%
BUY	No change	Buy 1	Increase 1	396	7.26%

Different decision trees for the NL model can be constructed depending on how the unobserved attributes are shared between the alternatives in the error terms. Four possible two-level NL models are considered in this paper, as presented in Fig. 3 to Fig. 6. In the NL model A (see Fig. 3[3]; Model A hereon), the alternatives are classified according to their buy/sell decisions, which gives rise to three branches at the higher level: Sell, Replace, and Buy. The first branch includes the decisions that do not involve buying behavior, including D2, D1 and SQ; the second branch includes all replacement behaviors: RPD1 and RP; the third branch is a degenerated branch, which is a branch or nest contains only one alternative.

[3]D2 stands for decrease two cars, D1 stands for decrease one car, SQ stands for status quo, RPD1 stands for sell two cars and buy one car, RP stands for replacement, and BUY stands for buy one car.

This model tests whether selling behaviors (e.g., D2 and D1) are correlated and whether replacement behaviors (RPD1 and RP) are also correlated.

As shown in Fig. 4, the NL model B (Model B hereon) is modified based on model A by separating the SQ alternative from the Sell branch. Thus, the first branch of model B consists with pure selling behaviors, D2 and D1; the second branch contains all replacement decisions, RPD1 and RP; and the rest two of the branches are degenerative branches. This model also tests whether selling behaviors share common components in the error terms and whether RPD1 and RP are correlated with each other.

While Model A and Model B are constructed according to respondents' behavior, Model C and Model D are based on the change of the total number of vehicles owned in a household. Model C (see Fig. 5) has four branches. The first branch consists with all decisions that lead to a decreasing number of total vehicles; the rest three branches are all degenerated branches that representing replacement while sustains the number of vehicles, doing nothing, and buying a new vehicle.

Models D (see Fig. 6) is similar to model C as both models test whether the behaviors that lead to a decreased number of vehicles are correlated. Besides, model D also grouped the two alternatives that resulted in no changes to vehicle holding level: SQ and RP. The buying decision itself is a degenerated branch.

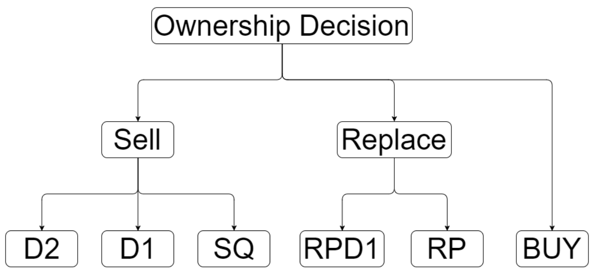


Figure 3: Nest Structure A

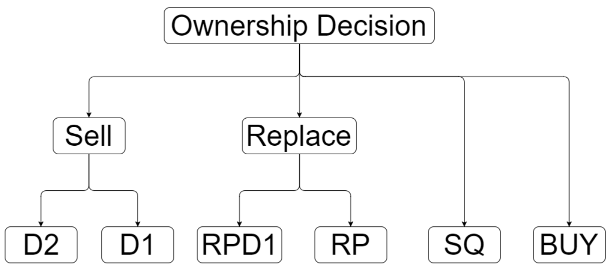


Figure 4: Nest Structure B

4. Analysis and results

4.1. Model description and selection

As mentioned previously, a series of NL models were estimated using the stated choice data. In this section, we present the process of selecting the models. Four nested structures

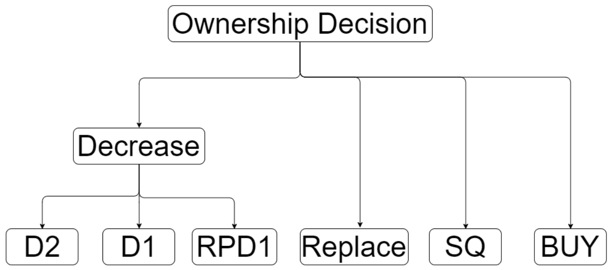


Figure 5: Nest Structure C

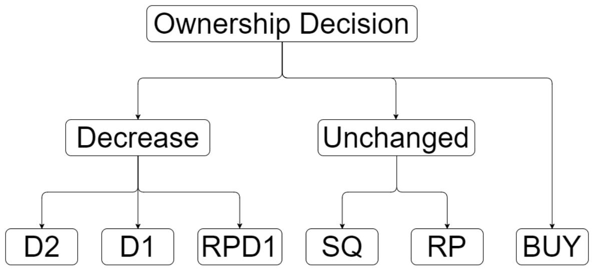


Figure 6: Nest Structure D

(see Fig. 3 – Fig. 6) for the car-sharing availability model and four for car-sharing effects model, thus eight models in total, are estimated using Nlogit (Greene, 2016), a statistical package specialized in discrete choice modeling. The summary statistics for the different NL models, which represent the model performance, are given in Table 7 and Table 8. Walds tests were used to test the logsum values, more specifically, the null hypothesizes of Wald test one and two are the logsum values are statistically equal to zero and one, respectively.

As shown in Table 7, one or both of the logsum values in models B, C, and D is statistically greater than one, suggesting the inconsistency with the theoretical derivation, and these models are rejected. In contrast, the logsum values of the two nests in Model A are between zero and one, which implies the correlation among the alternatives within the nests. In addition, amongst all the four models, Model A has the largest R square, and the NL model base on structure A statistically outperformed MNL model according to the likelihood ratio test. The likelihood ratio test uses the Chi-squared test statistic that can be obtained through $-2 \times [LL_{MNL} - LL_{NL}]$. The MNL model can be rejected if the value is greater than the critical value of with degrees of freedom equal to the number of logsum parameters for the Chi-square distribution. The Chi-squared test statistics for this model is 27.495[4], which is greater than the critical value of 5.99 (95%), thus rejecting the MNL model. Therefore, Model A was selected as the best model for modeling car-sharing availability's impact on vehicle ownership. The modeling results are presented later.

Regarding the car-sharing effects models, the summary statistics are given in Table 8. Both decision tree A and B are valid because the logsum values of the branches are all

[4]The log-likelihood value of the base MNL model is -5164.8475 and the log-likelihood value for the NL model A is -5151.1. Chi-squared test statistics $= -2 \times [(-5164.8475) - (-5151.1)]$

Table 7 Summary statistics for different car-sharing availability models

Model	R square	Nests	Logsum	Wald test 1	Wald test 2
MNL	0.11	-	-	-	-
NL model A	0.532	Nest 1	0.527	3.3	-2.96
		Nest 2	0.688	12	-5.47
NL model B	0.413	Nest 1	1.087	15.42	1.24
		Nest 2	0.836	14.67	-2.88
NL model C	0.411	Nest 1	1.181	20.92	3.21
NL model D	0.475	Nest 1	1.244	17.15	3.34
		Nest 2	1.168	10.48	1.51

statistically between zero and one, however, specification A is selected due to the highest R-squared value. Model C is rejected because the null hypothesis that the logsum is not different from one could not be rejected, thus collapses to MNL model Model D is also rejected due to the same reason (first logsum value equals one). Similarly, the performance of NL model A is statistically better than the MNL model because the likelihood ratio test statistic of this model is 11.19[5], which exceeds the critical value of 5.99 (95%). The modeling results will be presented below.

Table 8 Summary statistics for different car-sharing effects models

Model	R square	Nests	Logsum	Wald test 1	Wald test 2
MNL	0.109	-	-	-	-
NL model A	0.527	Nest 1	0.377	1.61	-2.66
		Nest 2	0.701	7.23	-3.08
NL model B	0.407	Nest 1	1.138	9.03	1.1
		Nest 2	0.943	8.73	-0.53
NL model C	0.408	Nest 1	1.142	13.6	1.69
NL model D	0.471	Nest 1	1.028	11.82	0.32
		Nest 2	0.628	4.03	-2.38

4.2. Model performance

As shown in Table 7 and Table 8 structure A (see Fig. 3) is the best performing specification, with the logsum parameters significantly between zero and one, for the two NL models. The overall performances of of both the models are statistically significant at a 99% confidence level, with the reasonably good McFadden Pseudo R-squared values of 0.5318 (see Table 11) and 0.527 (see Table 12), repetitively, as it is suggested that a Pseudo R2 value greater than 0.3 is an indication of a decent model fit for a discrete choice model and

[5]The log likelihood value of the base MNL model is -2627.201 and the log likelihood value for the NL model A is -2621.605. Chi-squred test statistics $= -2 \times [(-2627.201) - (-2621.605)]$

a Pseudo R2 between 0.4 and 0.6 reflect an excellent model fit (Dissanayake and Morikawa, 2002; Jovicic and Hansen, 2003; Ortuzar and Willumsen, 2002). For both models, the logsum values of both Sell and Replace branches are statistically between zero and one, suggesting the non-zero correlation among the alternatives within the same nest, which thus validates the NL structure (Koppelman and Bhat, 2006).

In addition to the R-squared, another useful tool to determine model performance is the contingency table, which effectively compares the choice outcomes at an aggregated level (Hensher et al., 2015). Table 9 and 10 present the contingency tables for the two models in this study. The columns represent the frequency of choices that are predicted to be made for each alternative, while the rows represent the number of choices actually made by the respondents for each alternative. The elements on the diagonals of the two tables counted the total number of times that the choices have been correctly predicted by the models for each alternative, whereas the off-diagonals numbers represent the total number of incorrectly predicted choices for each alternative. We can simply sum up the diagonal elements and divide them by the total number of choices made to generate the rates of correct predictions. The frequencies that the two models correctly predicted the choices made by respondents are 60.83% and 60.55%, respectively. Given the novelty of some alternatives in this study (e.g., AVs and SAVs), it is should not be surprising to see that the percentage of correct predictions are not high. Besides, as one of the early studies in this direction, the main motive is to provide some insights and advance our understanding on consumers' preference towards the new mobility options.

Table 9 Contingency table for car-sharing availability model

	D2	D1	SQ	RPD1	RP	BUY	Total
D2	**6**	19	92	1	20	3	141
D1	1	**270**	527	4	84	10	896
SQ	1	80	**2817**	0	107	43	3048
RPD1	0	7	109	**2**	37	2	157
RP	0	71	499	0	**143**	18	731
BUY	1	9	300	3	56	**27**	396
Total	9	456	4344	10	447	103	5369

4.3. Impact of car-sharing availability (car-sharing availability model)

Table 11 summarizes the results of the model based on the decision tree structure A. Doing nothing (SQ) is set as the base alternative, the coefficients of bought two-wheeler, sold two-wheeler and age are estimated as generic. As shown in this table, the households' decisions on the ownership of two-wheelers (both buy and sell) are positively correlated with the alternatives, suggesting that households that change their two-wheeler ownership are also more likely to change their households' vehicle ownership. As expected, age is negatively associated with all behaviors, the elder respondents are less likely to change the ownership status, suggesting that the probability is low for elder respondents to neither purchase nor sell their households' vehicles.

Table 10 Contingency table for car-sharing effect model

	D2	D1	SQ	RPD1	RP	BUY	Total
D2	**2**	9	48	2	6	4	71
D1	3	**125**	282	3	45	6	464
SQ	1	51	**1425**	1	33	15	1526
RPD1	0	3	54	**8**	12	7	84
RP	0	17	252	7	**68**	10	354
BUY	0	10	150	5	32	**11**	208
Total	6	215	2211	26	196	53	2707

The possibility of selling the existing vehicles increases as the total vehicle interior capability increase, this is understandable, and for example, if two vehicles owned by a household are large/family vehicles, they are likely to reduce their vehicle holding levels. Besides, the likelihood of reducing one vehicle is higher for more educated respondents, and households with more private vehicles garaged are more willing to reduce only one but not two of their current vehicles. The average refuel distance is negatively associated with D1, suggesting that the probability of selling one existing vehicle decreases if respondents are live in a disadvantaged area where refuel infrastructures are far from their home and not convenient to use. Also, larger families with members greater or equal to three are unlikely to dispose their vehicle.

In terms of the replacement behaviors including RPD1 (sell two and buy one) and RP (sell one and buy one). As seen in this table, if the estimated resale price of the current vehicle(s) exceeds the purchase price of a new vehicle, respondents are more likely to replace one or two of their current vehicle(s) with a new car. When considering to streamline or upgrade the fleet of family cars (i.e., RPD1 or RP) respondents are less likely to choose to replace the current vehicle(s) with a petrol-powered vehicle. The potential policies such as free registration fee, free EV public charging, and free use of transit and bus lanes could effectively increase the probability of vehicle transaction behaviors. Also, the education level is positively correlated with the likelihood of vehicle replacement, and the respondents tend to replace a current vehicle with a relatively smaller future vehicle. Moreover, in a more developed market with higher car-sharing market share, consumers are willing to stick with their current fleet of vehicles, probably because their occasional use of other types of vehicles could be fulfilled by car-sharing.

As expected, households with more family members (e.g., three or more members) are more likely to acquire a new vehicle, whereas, families with a larger number of vehicle holdings are less likely to add an additional car to their fleets. Moreover, the likelihood of purchasing a new car is negatively correlated with both vehicle purchasing price and operating cost. Interestingly, Australian respondents are environmentally friendly as they are more willing to purchase a greener car. Besides, it could be expected that the government incentives, which includes tax rebate, toll road discount and free use of transit and bus lanes could increase the new car sales significantly.

More importantly, the car-sharing option has no impact on respondents' private vehicle decision. It can be seen in this table, whether the car-sharing information is presented to respondents or not does not have a statistically significant influence on respondents' vehicle ownership decisions including acquiring, disposing, or replacing vehicles.

Table 11 The nested logit model with full sample (N=5369)

Variable	Coefficient	z-value	P-value
D2	-3.671***	-8.53	.0000
Bought two-wheeler	1.58***	14.33	.0000
Sold two-wheeler	1.108***	7.76	.0000
Age	-.195***	-7.67	.0000
Interior capability	.557***	13.83	.0000
Total private car	-.388**	-2.47	.0136
Car sharing option	.026	.69	.4913
D1	-1.66***	-8.5	.0000
Bought two-wheeler	1.58***	14.33	.0000
Sold two-wheeler	1.108***	7.76	.0000
Age	-.195***	-7.67	.0000
Interior capability	.557***	13.83	.0000
Education	.11***	4.17	.0000
Household size ≥ 3	-.235***	-2.67	.0077
CV average refuel distance	-.55***	-12.58	.0000
Total private car	.23***	4.28	.0000
Car sharing option	.011	0.64	.5222
RPD1	-1.197***	-5.64	.0000
Bought two-wheeler	1.58***	14.33	.0000
Sold two-wheeler	1.108***	7.76	.0000
Age	-.195***	-7.67	.0000
Difference in price: CV price - FV price	.004***	2.87	.0041
FV petrol powered car	-.552***	-2.24	.0251
FV free registration fee	.685***	2.72	.0064
FV free EV public charging	.788**	2.16	.0304
Car sharing option	.034	.81	.4168
RP	-.709**	-2.6	.0092
Bought two-wheeler	1.58***	14.33	.0000
Sold two-wheeler	1.108***	7.76	.0000
Age	-.195***	-7.67	.0000
Education	.177***	4.77	.0000
FV petrol powered car	-.287***	-1.97	.0488
Difference in price: CV price - FV price	.007***	3.22	.0013
Interior capability: FV - CV	-.372***	-8.7	.0000
FV free registration fee	.378***	2.21	.0269

FV free EV public charging	.48*	1.9	.0571
FV free use of transit + bus lanes	0.384**	2.37	.018
Car-sharing market share	-.088*	-1.71	.0867
Car sharing option	-.026	-.94	.3475
BUY	-.303	-.84	.4029
Bought two-wheeler	1.58***	14.33	.0000
Sold two-wheeler	1.108***	7.76	.0000
Age	-.195***	-7.67	.0000
Household size ≥ 3	.443***	3.78	.0002
FV price	-.022***	-4.18	.0000
FV environmental friendliness	.109***	1.72	.0848
FV average operating cost	-.096**	-2.05	.0404
Total private car	-.294***	-3.86	.0001
Tax rebate	.357**	2.31	.0207
Toll road discount	.323**	2.1	.0356
Free use of transit + bus Lanes	0.35**	2.17	.0299
Car sharing option	.014	0.56	.5744
Sell	.527***	3.34	.0008
Replace	.688***	12.02	.0000
BUY	1		

Full information maximum likelihood (FIML) Nested Multinomial Logit model.
Log-likelihood= -5151.1; Restricted log-likelihood = -11001.7953.
McFadden Pseudo R-square = 0.5318; AIC = 10384.2, AIC/N=1.934.
Normalization type = RU1. Number of parameters estimated = 41

4.4. Impact of car-sharing attributes(car-sharing effect model)

The car-sharing availability model, based on the full sample (N=5,369) above, suggests that the car-sharing option appears to have no impact on respondents' vehicle ownership decision-making process. However, the influence of each car-sharing attribute remains unknown. Specifically, when making ownership decisions, would respondents completely ignore the car-sharing factors or would they consider some specific factors? In this section, the car-sharing effects model, focusing on the scenarios in which the car-sharing related information is always provided (N=2707), is presented to explicitly examine whether respondents are affected by some of the car-sharing attributes.

The results of the car-sharing effects model based on specification A (see Fig. 3) are summarized in Table 12. Results of this model are consistent with the car-sharing availability model (see Table 11) based on the full sample. Respondents' vehicle ownership decisions including purchasing, reselling, replacing or doing nothing are largely dependent on the vehicle specific attributes and households' socio-demographic factors, however, the car-sharing specific variables appear to have moderate impacts on respondents' decision. Similarly, respondents who change ownership status of two-wheelers are also more likely to change their household vehicle ownership, and the elder respondents are more likely to stick with their current vehicles.

As seen in this table, respondents are more likely to sell two vehicles if the total vehicle interior capability is higher. More educated respondents or families with a larger number of vehicles are more willing to dispose one of their households' vehicle(s). Households with more family members are less likely to reduce their vehicle holdings by two, as more vehicles are needed to fulfill their mobility demand, and the probability of reducing a vehicle is low for respondents in disadvantaged areas. In addition, car-sharing with long access distance from home significantly reduce customers' willingness to us, which in turn reduce the possibility of disposing current vehicles. However, respondents in Australia appear to favor large or petrol-powered shared vehicles, as these attributes are negatively associated with their probability to reduce their current cars.

Regarding replacement behavior, when the resale price of the current vehicles exceeds the purchase price of a considered vehicle or the future vehicle comes with a registration fee exemption, respondents are willing to replace two current vehicles with a new car; however, they are unlikely to replace their current vehicle with a traditional petrol-powered vehicle. Similarly, respondents tend to replace one of their current cars with a smaller one and the purchase price of future cars has negative impacts on their likelihood of vehicle replacement. Concerning the effects of car-sharing, if the shared car is allowed to use transit and bus lane for free, respondents are unlikely to reduce their vehicle ownership, and the access distance from work appears to have negative impacts on the respondents' replace with disposal decision. Moreover, respondents are more likely to replace (and decrease) their vehicles if SUV or micro vehicles are available from the car-sharing operators.

In addition, respondents' intention of buying an additional vehicle is negatively associated with the purchase price and operating cost, however, is positively associated with the environmental friendliness. As expected, households with three or more family members are more likely to buy an FV, whereas families with more current vehicles are less likely to acquire an additional one. Moreover, car-sharing operating cost and driving range are negatively associated with new vehicle purchase behavior, and respondents are more likely to buy their new car if the shared car available to them is a micro-size vehicle.

In terms of the household-specific variables, more educated respondents are more likely to resell or replace one of their current vehicles. Respondents who had longer average refuel distance are likely to keep their current vehicles and less likely to purchase new vehicles than those who lived in the advantaged area. As expected, households with three or more family members are more likely to buy an FV and less likely to reduce one of their current vehicles.

In summary, as shown in Table 12, respondents' decisions are likely to be influenced by some of the car-sharing specific factors including operating cost, market share, driving range, fuel type, vehicle type, and access cost. Interestingly, car-sharing cost and driving range are found to have statistically significant impacts on respondents' vehicle purchasing decision, however, had no impacts on disposal decisions. While the availability of car-sharing had no impacts on respondents' behavior, the car-sharing specific attributes presented had a moderate influence on the choice probabilities, suggesting that the prior studies may have overestimated the impact of car-sharing availability.

Table 12 The nested logit model for the sample with car-sharing option (N=2707)

Variable	Coefficient	z-value	P-value
D2	-2.756***	-8.15	.0000
Bought two-wheeler	1.558***	10.82	.0000
Sold two-wheeler	.952***	5.21	.0000
Age	-.203***	-5.95	.0000
Interior capability	.188***	4.62	.0000
Household size ≥ 3	-.273**	-2.31	.0209
CS access distance from home	-.044***	-3.23	.0013
CS large vehicle	-.817**	-2.37	.0178
D1	-1.169***	-4.43	.0000
Bought two-wheeler	1.558***	10.82	.0000
Sold two-wheeler	.952***	5.21	.0000
Age	-.203***	-5.95	.0000
Interior capability	.188***	4.62	.0000
Total private car	.393***	5.37	.0000
Education	.116***	3.17	.0015
CV average refuel distance	-.535***	-9.00	.0000
CS petrol powered vehicle	.571***	4.17	.0000
RPD1	-1.267***	-2.97	.0030
Bought two-wheeler	1.558***	10.82	.0000
Sold two-wheeler	.952***	5.21	.0000
Age	-.203***	-5.95	.0000
Difference in price: CV price - FV price	.012***	2.60	.0092
FV petrol powered car	-1.274***	-3.23	.0012
FV free registration fee	.568*	1.68	.0936
CS free use of transit + bus lanes	-.523**	-1.98	.0482
CS access distance from work	-.033*	-1.95	.0509
CS SUV	1.155***	2.91	.0036
CS micro vehicle	.834***	2.62	.0089
RP	-1.173***	-2.91	.0036
Bought two-wheeler	1.558***	10.82	.0000
Sold two-wheeler	.952***	5.21	.0000
Age	-.203***	-5.95	.0000
Education	.164***	2.95	.0032
FV petrol powered car	-.49**	-2.28	.0228
Interior capability: FV - CV	-.265***	-4.42	.0000
FV price	.013***	3.01	.0026
CS micro vehicle	.465**	2.44	.0146
CS environmental friendliness	.175*	1.85	.0637
BUY	1.051*	1.68	.0930
Bought two-wheeler	1.558***	10.82	.0000

Sold two-wheeler	.952***	5.21	.0000
Age	-.203***	-5.95	.0000
Total private car	-.223**	-2.13	.0335
Household size ≥ 3	.519***	3.15	.0016
FV price	-.032***	-4.43	.0000
FV environmental friendliness	.211**	2.36	.0184
FV operating cost	-.14**	-2.12	.0341
CS operating cost	.111*	1.69	.0919
CS driving range	-.12*	-1.92	.0554
CS micro vehicle	.308*	1.82	.0689
Sell	.377	1.61	.1083
Replace	.701***	7.26	.0000
BUY	1		

Full information maximum likelihood (FIML) Nested Multinomial Logit model.
Log-likelihood= -2621.605; Restricted log-likelihood = -5541.782.
McFadden Pseudo R-square = .527; AIC = 5321.2, AIC/N=1.966.
Normalization type = RU1; Number of parameters estimated = 39

5. Policy implications

The findings presented here usefully build upon the existing literature by underscoring the crucial role of policy. Previous studies that focus on car-sharing users only usually find a positive influence of car-sharing on vehicle ownership (i.e., consumers are likely to reduce household vehicles after joining car-sharing). However, it is intrinsically difficult to reduce car use and car ownership (Graham-Rowe et al., 2011), and comparing the results of the two models in this study allows us to identify the possibly over-optimistic results in existing studies. As evidenced by the present study, the general consumers are unlikely to change their car ownership status simply due to the availability of car-sharing (i.e., the first model), whereas the second model shows that if car-sharing attributes are put in front of the respondents closely, the consumers' behavior might be nudged or implicitly influenced by car-sharing related factors. Based on this, we believe it is reasonable to expect that education and awareness campaigns might facilitate car-sharing adoption, and thus increase car-sharing's impact on car ownership. This is not surprising, as in the real-world, even if the car-sharing option is available, most people tend to not consider it while making car ownership decisions. Therefore, beyond merely making car-sharing programs available, our evidence suggests that there is an urgent need for policies that actively make car-sharing schemes attractive to consumers. Some specific policy implications can be considered from this study.

Firstly, prior studies have shown that respondents with car-sharing experience are likely to significantly reduce their car ownership (Martin and Shaheen, 2011; Martin et al., 2010; Katzev, 2003). On the one hand, policy makers should recognize that the results of these prior studies may tend to over-estimate the impact of car-sharing availability on vehicle ownership given potential self-selection bias, for example, up to 60% decrease in private vehicles was reported in Katzev (2003).

On the other hand, this present study highlights the importance of the car-sharing experience, given car-sharing's minimal impact on private car ownership may simply be the result of respondents' unfamiliarity with car-sharing. Based on the results of the two models in this study, it could be argued that education and awareness campaigns might facilitate car-sharing adoption. More specifically, while our car-sharing availability model shows no significant impact of car-sharing availability on general public's car ownership decision, our car-sharing effect model reveals that when we focus on the SP scenarios in which car-sharing is available, several car-sharing attributes appear to have significant impact on their car ownership decisions, which implies that if we can help the general public to know more about car-sharing (e.g., how it works, what are its benefits to individuals and society, etc.) through some well-designed education and awareness campaigns, car-sharing could exert more influence on people's car ownership decision than what is currently revealed in our car-sharing availability model. Also, as shown in Jensen et al. (2013), a significant change of consumers' preferences for the electric vehicle could be observed after they had experienced driving an electric vehicle. The same effect could be expected in car-sharing and SAVs. Besides providing car-sharing experience to potential consumers, education campaigns designed to promote the general public's awareness might be another effective way to increase the general public's preference towards car-sharing and to fully realize car-sharing's benefits to the society. More specifically, through education, consumers might better understand the underlying costs of travel and become more appreciative of the low car-sharing costs. For instance, in Nordlund and Garvill (2003)'s field study, compared to a control group, a policy intervention that increased the awareness of alternative travel modes and the awareness of the context of the pre-planned trips was applied to the experimental group. The results indicated that respondents in the experimental group effectively reduced their travel times. Similar effects were also found in Alcott and DeCindis (1991), whereby psychological intervention (i.e., education and awareness rising) facilitated the adoption of car-pool. Also, Anable et al. (2004) argued that education and awareness raising lead to reduced automobile use. Hence, appropriate policies and education programs to provide consumers with virtual experience and increased awareness can potentially facilitate the adoption of car-sharing and SAV, leading to reductions in both car use and car ownership.

In addition to education and awareness campaigns, pricing is also important. Car-sharing programs are available in many cities around the world with various degrees of success. A big challenge that policy makers face is to encourage a mode shift from private vehicles to car-sharing. A possible way to increase car-sharing's attractiveness and eventually induce mode shift is to adopt MaaS (The Economist, 2016) model (Mobility as a Service) which combines different travel modes and seamlessly integrates them into a subscription program. The MaaS program can significantly further improve car-sharing's flexibility and affordability. For example, with a similar cost of vehicle ownership (e.g., \$400/month), one can get access to a wide range of mobility options including public transport, taxi, car-sharing, ferry, etc. This kind of innovative solution can be appealing to consumers, and possibly lead to reduced private car ownership and increased use of car-sharing.

The elasticity theories back this up, the intuition behind these subscription programs is to decrease the cost of a bundle of alternative travel modes. As shown by Hensher and King (1998), an increase of 10% in public transit fare (train and bus) causes 1.96% increase in car sales. In the U.S. context, Mcmullen and Eckstein (2011) argue that the long-run elasticities between public transit and private vehicle usage are 0.0228 (higher transit usage, fewer car travels). Based on the results of the stated choice experiments, Haboucha et al. (2017) concluded that increasing customers' awareness of SAVs and the associated benefits, along with raising the costs of regular cars, could facilitate SAV adoption. Other factors including fuel price (-0.2 to 0.0), income (0.75 to 1.25), taxation (-0.08 to -0.04) population density (-0.7 to -0.2), etc. were also appear to influence consumer car stock choices, calculated elasticities in the parentheses (Litman, 2019). The results of this study are consistent with the literature, for example, based on the estimation of elasticities, 1% increase in new vehicle purchase price, future vehicle operating cost, or car-sharing driving range is likely to reduce 0.79%, 0.56% 0.21% reduction in the probability of buying a new car (other factors remain constant), respectively; and an increase of 1% car-sharing access distance could possibly reduce the possibility of disposing two private cars by 0.44%. Therefore, changing the fare (e.g., operating and parking cost), quality (e.g., premium car or access distance), ease of use (e.g., park in non-designed lots) of car-sharing, or implement policies that increase the cost of vehicle ownership (e.g., congestion fee) could facilitate car-sharing adoption and car stock reduction.

6. Conclusion

Pronounced growth in rates of vehicle ownership around the world continues to perpetuate a series of economic and environmental issues. Car-sharing has received substantial interest in the last few decades as a potential solution to these issues. Despite car-sharing's promise on these fronts, there have been limited quantitative studies investigating the impacts of car-sharing and SAVs on vehicle ownership. Most prior vehicle ownership studies have largely failed to consider car-sharing and SAVs, and those few studies that have been specifically focused on car-sharing (Martin et al., 2010; Fagnant and Kockelman, 2014; Chen et al., 2016) have tended to focus on RP data, or been based on the simulated cost-saving analysis. For example, by comparing the size of households' fleet of private vehicles before and after joined car-sharing, some studies have concluded that a significant reduction in private vehicles can be achieved thanks to car-sharing (Firnkorn and Müller, 2012; Martin and Shaheen, 2011). However, studies that rely on RP data solely, for example, data from the car-sharing operators, could suffer from sample selection bias or self-selection bias, thus leading to less robust results. In addition, studies drawing solely on RP information are not capable of investigating the impacts of emerging technologies like autonomous vehicles in car-sharing

This paper contributes to this knowledge gap by providing population-based estimates of the impact of car-sharing program availability on personal vehicle ownership. Towards this end, car-sharing's impacts on personal vehicle ownership was analyzed from two aspects: firstly, the impact of car-sharing program availability on personal vehicle ownership; and secondly, the influence car-sharing availability and attributes on personal vehicle ownership. Data collected from a national survey of respondents from major Australian cities was used, and to account for correlations amongst different transport modes, a series of Nested Logit (NL) modles were estimated and compared. Unlike many prior studies, this survey is based on a sample of the general public rather than car-sharing user groups. To avoid the problem caused by offering as alternatives car-sharing and buying a 2^{nd} car as incompatible (Kim et al., 2017), the present study establishes car-sharing as background information to remind respondents as to the availability and characteristics of the car-sharing or SAVs. This design, which more closely mimics reality, is expected to be more realistic, as respondents' car-sharing behavior should be indirectly related to their vehicle ownership choices. In addition, the impact of shared autonomous vehicles on vehicle ownership has also been investigated from the consumers' perspective.

Based on the modelling results of car-sharing availability and car-sharing effects, we found that the availability of car-sharing appear to have no influence on respondents' vehicle ownership decisions, while its associated attributes had a moderate impacts. Overall, our findings differ with those reported in prior studies, however, this is not surprising given that many previous studies have analyzed data collected from early adopters of car-sharing (i.e., either car-sharing users or operators). This group of respondents is generally found to be more environmentally conscious, less automobile-dependent, and more willing to commit to sustainable activities than the average population (Costain et al., 2012; Martin et al., 2010). In contrast, this study examined a sample drawn from the general public, and consequently, did not detect a significant impact of car-sharing availability on private car ownership.

The results of this study suggest that policy-makers or related stakeholders should use the existing forecasts with caution. Education programs could be provided to consumers to increase their awareness of car-sharing and to experience the service, based on advice from other studies. Also, to facilitate car-sharing adoption, more innovative and creative ways (e.g., MaaS) are expected to attract consumers. Combing necessary education, trial programs and more efficient and optimized schemes, the adoption of car-sharing might be effectively increased.

Despite the fact that this paper sought to address methodological shortcomings in prior investigations, we acknowledge that it has weaknesses of its own. Firstly, it should be recognized that the results of this current study are based on stated preference data; which have been criticised for their lack of reliability as people's actual choices might be inconsistent with stated choices. Additionally, limitations of the nested logit model, with "nests" determined by researchers, may result in clusters of alternatives associated in unobserved ways. Specifically, a five alternative choice set can have a maximum of 50 potential two-level nesting structures, whereby the analyst's judgment affects the model structure. In addition, as mentioned above the respondents were asked to do the experiments repeatedly, however, the panel impacts stay unanswered because the NL model cannot represent heterogeneity in respondents' preferences, thus, fails to capture customers' potential taste variations. Moreover, as mentioned above, transaction timing is considered one of the important factors influencing consumers' vehicle ownership decisions, however, our data does not contain such information, which makes it impossible to incorporate it in our models.

Furthermore, we also tried the multivariate formulation, which is an efficient way to deal with correlations among alternatives, at the early stage including simultaneous probit model (Mallar, 1977) and the multivariate probit model (Chib and Greenberg, 1998), these models address the correlated alternatives by allowing the error terms to be freely correlated, thus can be used to estimate a group of correlated binary outcomes (buy/sell) simultaneously. These models have been frequently and successfully used in the transport research literature (Choo and Mokhtarian, 2008; Viswanathan et al., 2000; Golob and Regan, 2002). However, these models could not present the change in vehicle ownership (e.g., increase or decrease). In addition, to incorporate panel impacts and to explore the potential taste variation, we also tried mixed logit model; however, due to the large sample size and complexity of the experiments, it is time consuming and computationally intensive to estimate the model. Therefore, we adopted the NL model at the end since it better describes the correlated buy/sell behaviors and the change of vehicle holdings with a nest structure.

While our study suggests that the availability of car-sharing and SAVs do not have significant impacts on respondents' vehicle ownership choices, there is significant evidence to support the substantial potential impact these new forms of mobility could have on households' mode choices (Zhou et al., 2020). Further work is needed to understand how consumers can be better engaged and informed in order to trial car-sharing programs, and how government and private sector transport operators can work collectively to develop attractive pricing models that, combined with awareness campaigns, help cities capitalize on the significant potential benefits of these new forms of mobility.

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Appendix A.

Table A.1 shows the model outputs of the model based on only observations that car-sharing presented (column 2) and the model with full sample (column 3), both models aim to answer research question two (RQ 2). As seen from this table, two models are highly consistent, in terms of both the magnitude and significance of the coefficients. However, this combined model dose not allow us to directly answer RQ 1: whether the appearance of CS has impacts on private vehicle ownership or not? Therefore, we believe that more information could be extracted from the data with two separate models.

Table A.1 The nested logit model regarding RQ 2 (investigating the impact of CS attributes)

Variable	**Model 2 above (Table 11) N=2707**	**Model with interactions N=5369**
D2	-2.756***	-4.51***
Bought two-wheeler	1.558***	1.545***
Sold two-wheeler	.952***	1.068***
Age	-.203***	-.199***
Interior capability	.188***	.561***
Household size ≥ 3	-.273**	-.215**
CS access distance from home	-.044***	-.032***
CS large vehicle	-.817**	-.949***
D1	-1.169***	-1.711***
Bought two-wheeler	1.558***	1.545***
Sold two-wheeler	.952***	1.068***
Age	-.203***	-.199***
Interior capability	.188***	.561***
Total private car	.393***	.258***
Education	.116***	.112***
CV average refuel distance	-.535***	-.584***
CS petrol powered vehicle	.571***	.565***
RPD1	-1.267***	-1.279***
Bought two-wheeler	1.558***	1.545***
Sold two-wheeler	.952***	1.068***
Age	-.203***	-.199***
Interior capability	.188***	-
Difference in price: CV price - FV price	.012***	.00443***
FV petrol powered car	-1.274***	-.734***

FV free registration fee	.568*	.469**
CS free use of transit + bus lanes	-.523**	-.519**
CS access distance from work	-.033*	-.021
CS SUV	1.155***	.898**
CS micro vehicle	.834***	.661**
RP	-1.173***	-.87***
Bought two-wheeler	1.558***	1.545***
Sold two-wheeler	.952***	1.068***
Age	-.203***	-.199***
Education	.164***	.177***
FV petrol powered car	-.49**	-.358**
Interior capability: FV - CV	-.265***	-.37***
FV price	.013***	.008***
CS micro vehicle	.465**	.346*
CS environmental friendliness	.175*	-.002
BUY	1.051*	-.07
Bought two-wheeler	1.558***	1.545***
Sold two-wheeler	.952***	1.068***
Age	-.203***	-.199***
Total private car	-.223**	-.301***
Household size ≥ 3	.519***	.43***
FV price	-.032***	-.021***
FV environmental friendliness	.211**	.099
FV operating cost	-.14**	-.115**
CS operating cost	.111*	-.033
CS driving range	-.12*	-.093
CS micro vehicle	.308*	.262
Sell	.377	.436***
Replace	.701***	.657***
BUY	1	

*, **, and *** for 90%, 95%, and 99% confidence levels respectively.