# Manuscript Details

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| **Manuscript number** | TRC_2018_1167_R2 |
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### Abstract

Free-floating carsharing (FFCS) fleets are inherently volatile spatio-temporally, which presents both a logistical challenge for operators and a service reliability issue for customers. In this study we present a stated-choice survey to investigate the attractiveness to customers of two mechanisms for managing fleet volatility: Virtual Queuing (VQ) and Guaranteed Advance Reservations (GAR). We investigate socio-demographic features and “Big Five” personality traits that are associated ceteris paribus with choosing to use the existing FFCS service model, willingness-to-pay (WTP) for VQ and GAR, and risky-choice behaviour under the uncertainty of FFCS systems. Data (n=289; 232 employed in analysis) are sourced from existing users of a FFCS service in London, UK. Within the survey context, we found that customers are on average not willing to pay for VQ (i.e. negative WTP), however have £0.54 per journey WTP for GAR, with low-frequency FFCS users and users scoring highly on the Big Five “Conscientiousness” dimension having larger WTP for GAR. When analysing the two dimensions of uncertainty, we found that respondents exhibit risk-seeking behaviour towards price and weaker and insignificant risk-aversion towards walking time. This pattern holds across the three standard model types of nonlinear risky choice behaviour that we investigated. The results are intended to be useful both to policymakers and carsharing operators who are likely, as the industry matures, to seek mechanisms to differentiate their service offers to better serve individual market segments with distinctive characteristics.



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| **Keywords** | free-floating carsharing; user-based relocation; virtual queueing; guaranteed advance reservation; stated-choice survey; risky-choice |



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| **Corresponding Author** | Chenyang Wu |
| **Corresponding Author's Institution** | Imperial College London |
| **Order of Authors** | Chenyang Wu, Scott Le Vine, Aruna Sivakumar, John Polak |
| **Suggested reviewers** | Jinhee Kim, Francesco Ciari, Mehdi Nourinejad, Yu Nie |


# Submission Files Included in this PDF

**File Name [File Type]**

Cover letter Part C _r2.docx [Cover Letter]

Response_r2 1.0.docx [Response to Reviewers]

PartC_highlights.docx [Highlights]

Traveller preferences FFCS allocation mechanisms 2.1.docx [Manuscript File]

Supp_mat.docx [Supplementary Material]

22th February 2019

Dear Professor Yin:

I have enclosed Revision #2 of manuscript TRC-2018_1167, titled: Traveller preferences for free-floating carsharing vehicle allocation mechanisms.

The revisions consist of correcting typographical errors and updating/adding relevant references.

Thank you for your consideration; we will look forward to your feedback.

Sincerely,
Chenyang Wu
Imperial College London
c.wu15@imperial.ac.uk

**Responses to Peer Reviewer Comments**

In this round of revision we have corrected remaining typos and checked/updated references. Details are contained on the following pages.

We have turned on ‘track changes’ in the revised manuscript, so that changes made in this round of revision can be readily identified.

<<Continues on next page>>

**Author responses follow each comment below:**

The authors have addressed all my comments satisfactorily. I only have few minor corrections:
- p.4, l.33: should be "supplementary material" instead of "appendix", right?
- p.5., l.1: "extensive**ly**"
- p.8, footnote 1: "... in a **<few (?)>** minutes..."
- p.21, l.1: "six" instead of "sixed"
- p.23, l.9: suggest "GAR" instead of "GA"

AUTHOR RESPONSE: We have corrected these typos.

Please make sure all references are up to date (e.g., consider possibly relevant papers, particularly those published in TR Part C that may have come out or are in press since the paper was initially submitted).

AUTHOR RESPONSE: We have added the following very recently published studies that are relevant to the topic:

1. Dill, Jennifer, Nathan McNeil, and Steven Howland. 2019. "Effects of Peer-to-Peer Carsharing on Vehicle Owners' Travel Behavior." *Transportation Research Part C: Emerging Technologies* 101: 70–78. https://doi.org/10.1016/j.trc.2019.02.007. (page 4, line 21)
2. Balac, Milos, Henrik Becker, Francesco Ciari, and Kay Axhausen. 2018. "Modeling Competing Free-Floating Carsharing Operators A Case Study for Zurich, Switzerland." *Transportation Research Part C* 98: 101–17. https://doi.org/10.1016/j.trc.2018.11.011. (page 4, line 22)
3. Balac, Milos, Francesco Ciari, and Kay W. Axhausen. 2017. "Modeling the Impact of Parking Price Policy on Free-Floating Carsharing: Case Study for Zurich, Switzerland." *Transportation Research Part C: Emerging Technologies* 77. Elsevier Ltd: 207–25. https://doi.org/10.1016/j.trc.2017.01.022. (page 4, line 22)
4. Huang, Kai, Gonçalo Correia, and Kun An. 2018. "Solving the Station-Based One-Way Carsharing Network Planning Problem with Relocations and Non-Linear Demand." *Transportation Research Part C: Emerging Technologies* 90: 1–17. https://doi.org/10.1016/j.trc.2018.02.020. (page 4, line 39)
5. Wang, Ling, Qi Liu, and Wanjing Ma. 2019. "Optimization of Dynamic Relocation Operations for One-Way Electric Carsharing Systems." *Transportation Research Part C: Emerging Technologies* 101: 55–69. https://doi.org/10.1016/j.trc.2019.01.005. (page 4, line 40)
6. Zha, Liteng, Yafeng Yin, and Zhengtian Xu. 2018. "Geometric Matching and Spatial Pricing in Ride-Sourcing Markets." *Transportation Research Part C: Emerging Technologies* 92: 58–75. https://doi.org/10.1016/j.trc.2018.04.015. (page 23, line 29)

Highlights:

- Evaluation of two vehicle allocation mechanisms (virtual queueing (VQ) and guaranteed advance reservation (GAR)) in free-floating carsharing (FFCS)
- Proposes a stated-choice survey approach with two interactive uncertain attributes (journey cost and walking time)
- Identifies tastes to risk in the two uncertain attributes, using various risky choice formulations
- Analyses socio-demographic features and Big Five personality traits correlating with respondents' preference towards existing FFCS, VQ and GAR

# Traveller preferences for free-floating carsharing vehicle allocation mechanisms

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Chenyang Wu

PhD candidate, Centre for Transport Studies

Department of Civil and Environmental Engineering, Imperial College London

Email: c.wu15@imperial.ac.uk

Scott Le Vine

Assistant Professor, Department of Geography, SUNY New Paltz, United States

Research Associate, Centre for Transport Studies, Department of Civil and Environmental Engineering, Imperial College London

Email: s.le-vine@imperial.ac.uk

Aruna Sivakumar

Senior Lecturer, Centre for Transport Studies

Department of Civil and Environmental Engineering, Imperial College London

Email: a.sivakumar@imperial.ac.uk

John Polak

Professor, Centre for Transport Studies

Department of Civil and Environmental Engineering. Imperial College London

Email: j.polak@imperial.ac.uk

# Abstract

Free-floating carsharing (FFCS) fleets are inherently volatile spatio-temporally, which presents both a logistical challenge for operators and a service reliability issue for customers. In this study we present a stated-choice survey to investigate the attractiveness to customers of two mechanisms for managing fleet volatility: Virtual Queuing (VQ) and Guaranteed Advance Reservations (GAR). We investigate socio-demographic features and "Big Five" personality traits that are associated ceteris paribus with choosing to use the existing FFCS service model, willingness-to-pay (WTP) for VQ and GAR, and risky-choice behaviour under the uncertainty of FFCS systems. Data (n=289; 232 employed in analysis) are sourced from existing users of a FFCS service in London, UK. Within the survey context, we found that customers are on average not willing to pay for VQ (i.e. negative WTP), however have £0.54 per journey WTP for GAR, with low-frequency FFCS users and users scoring highly on the Big Five "Conscientiousness" dimension having larger WTP for GAR. When analysing the two dimensions of uncertainty, we found that respondents exhibit risk-seeking behaviour towards price and weaker and insignificant risk-aversion towards walking time. This pattern holds across the three standard model types of nonlinear risky choice behaviour that we investigated. The results are intended to be useful both to policymakers and carsharing operators who are likely, as the industry matures, to seek mechanisms to differentiate their service offers to better serve individual market segments with distinctive characteristics.

*Keywords*: free-floating carsharing, user-based relocation, virtual queueing, guaranteed advance reservation, stated-choice survey, risky-choice

# 1. Introduction

Providing users with adequate transport service using the relatively small number of vehicles in a carsharing fleet presents novel challenges, particularly in aligning the spatio-temporally unbalanced nature of user demand with vehicle supply (Jorge and Correia 2013; Nourinejad et al. 2015; Illgen and Höck 2018). To address this issue, free-floating carsharing operators can hire dedicated staff to rebalance the fleet distribution (operator-based relocation, see Fan (2013), Gambella et al. (2017), Nourinejad et al. (2015) and Weikl and Bogenberger (2015)). User-based relocation, which make use of users' spatial-temporal flexibility and engage them to relocate the vehicles, is also discussed in the literature (Jorge et al. 2015; Xu et al. 2018; Febbraro et al. 2018).

Another way of mitigating this imbalance is by introducing virtual queueing (VQ) and guaranteed advance reservation (GAR) mechanisms, which are common in fields with limited supply and volatile demand, such as communication network service, airlines, energy market and transport (McGinley et al. 2014; Faria and Vale 2011; You 1999). These two mechanisms have potential benefits for both the operator and the user: for VQ, the operator puts customers onto a waiting list rather than rejecting them, and these users may receive bespoke pricing for this type of transaction; for GAR, the operator receives information regarding users' demand in advance and can act accordingly, and users potentially benefit from greater reliability.

Both VQ and GAR are rarely adopted by FFCS operators today; GAR for planned journeys are typically permitted for round-trip but not for one-way FFCS services. A rare example of long-term GAR by a free-floating carsharing (FFCS) operator is Car2go's service in Chongqing (P.R. China), which operates only during specified major holiday periods (e.g. Chinese New Year). The vehicle usage must be a minimum of 24 hours, however, and the user must travel to a pre-defined location for vehicle pick-up/drop-off. This service therefore more closely resembles the temporary use of FFCS vehicles for services similar to traditional car rental, rather than the general provision of long-term advance reservations in FFCS. Several characteristics limit the practicality of VQ and GAR for FFCS services. For VQ, the operator needs to know (or be able to predict to a probability) where and when current users will leave their vehicles, and for GAR, the operator may need to block the usage of some vehicles (meaning foregone revenue) or deliver the vehicles to a user (meaning direct expenditure on staffing resources) that has been sold an advance reservation (see extended discussion in Molnar and Correia (2019)). However, operators today have relatively weak control of their fleet's minute-by-minute spatial distribution, and there is no published evidence of users' willingness-to-pay for VQ or GAR.

This study addresses the comparison of three operational models: 1) the existing FFCS service model, 2) VQ (which allows the respondent to reserve a FFCS vehicle that is currently in use and is expected to become available in a small number of minutes), and 3) GAR (which allows the respondent to reserve a FFCS for a journey to begin in several hours into the future). We present a stated-choice survey to collect users' response to VQ and GAR in FFCS and model attitudes toward them. The objectives of this study are:

(1) Develop a stated-choice (SC) survey to identify carsharing users' preference for VQ and GAR;
(2) Quantify preferences towards the existing (spontaneous-usage), VQ and GAR models;
(3) Quantify users' behaviour towards various dimensions of uncertainty (walking time and price) in GAR models.

The remainder of this paper is structured as follows: Section 2 reviews the existing research in carsharing operational management, reservation, user behaviour, risky-choice, and Big Five personality traits. Section 3 introduces the survey design, data collection process and the socio-demographic features of the empirical data. Section 4 presents the results of the behaviour modelling with discussions on the results. Section 5 concludes our main findings and possible directions for future research.

# 2. Background

Carsharing research includes various sub-branches, including demand modelling, user behaviour, system design and system management. In this section, we begin with studies of carsharing user behaviour modelling, followed by carsharing vehicle allocation mechanisms. The risky-choice behaviour and Big Five classification scheme for personality traits are discussed at the end of this section.

The intended contributions of this study are as follows:

(1) Identifying how FFCS users make trade-off between spatial-temporal flexibility (waiting and walking time) and price;
(2) Establishing willingness-to-pay for having queuing and reservation in FFCS;
(3) Quantifying the influence of socio-demographic features and the Big Five personality traits on user preferences toward existing FFCS, VQ and GAR services;
(4) Implementing an SC survey with two dimensions of uncertainties (walking time and price)
(5) Modelling FFCS users' risky-choice behaviour under these two dimensions of uncertainties.

## 2.1. Behavioural modelling of CS users

User behaviour relating to carsharing includes many aspects, including potential users' decision to pay for membership to the carsharing service (Prieto et al. 2017; Efthymiou et al. 2013), the usage of carsharing (Schmöller et al. 2015; Habib et al. 2012; Becker et al. 2017), the impact of carsharing on users (Becker et al. 2018; Le Vine and Polak 2016; Dill et al. 2019), and their attitudes toward the various features of the carsharing service (Balac et al. 2017; Balac et al. 2018).

Techniques to analyse user behaviour vary, with data generally sourced either from observed empirical behaviour (revealed preference, RP) or hypothetical situations (stated-choice, SC). The SC survey approach is most suitable for circumstances in which the actual or observed choices lack sufficient variation for statistical analysis, factors affecting the choice behaviour are correlated, or suitable RP data are unavailable due to the novelty of the service (Ortúzar and Willumsen 2011).

Studies employing SC surveys in the context of carsharing are summarised in the supplementary material. Study objectives are typically either about 'joining' a carsharing service or 'mode choice' with carsharing available as an option. The most common attributes to describe carsharing and competing travel modes are time (access time, travel time, waiting time, etc.) and price. Noteworthy studies that extend from the "time and costs" paradigm include Kim et al. (2017a, 2017b, 2017c). Kim et al. (2017a) considers both the uncertain availability of shared vehicles and the influence of the potential users' social network, Kim et al. (2017b) examines the impact of vehicle availability uncertainty on 'joining', and Kim et al. (2017c) focuses on the impact of activity duration and travel time uncertainty.

## 2.2. Carsharing vehicle allocation mechanisms

Vehicle allocation is one of the most extensively studied topics in carsharing research, especially one-way station-based carsharing (Huang et al. 2018; Nourinejad et al. 2015; Weikl and Bogenberger 2013; Wang et al. 2019). In these studies, the vehicle allocation work is done by staff who move vehicles from low-demand to high-demand areas, and this allocation mechanism is called operator-based system rebalancing.

Although less extensively studied, other vehicle allocation mechanisms are investigated. One mechanism is to utilise users' spatial-temporal flexibility. Example studies include Febbraro et al. (2018), Angelopoulos et al. (2018), and Ströhle et al. (2018). Febbraro et al. (2018) and Angelopoulos et al. (2018) only consider spatial flexibility, which assumes users are willing to change their intended pick-up/drop-off location when proper incentivisation is provided. Ströhle et al. (2018) considered not only spatial but also temporal flexibility, which require some users to shift their intended vehicle usage time. The authors then optimise the round-trip fleet size utilising users' spatial-temporal flexibility, and also employ SC survey data to identify the distribution of willingness-to-pay for the spatial-temporal flexibility.

The temporal flexibility of users is similar to the concept of queueing, which occurs naturally in many types of congestible networks, such as transport and telecommunication networks. Accepting advance reservations can both guarantee customers' access to the service and help the operator better plan their operation (by knowing demand patterns in advance). McGinley et al. (2014) compare the performance of queuing and reservation systems in telecommunication networks and determine the conditions under which reservation-mechanisms outperform queuing. Many transport networks also face a similar "reservation versus queuing" issue, with the relevant body of literature including studies of car rental (Oliveira et al. 2016), parking (Latinopoulos et al. 2017; Lei and Ouyang 2017), and freeway usage (Wong 1997; Su et al. 2013).

Prior studies discussing reservation in one-way carsharing include Boyacı et al. (2017), Alfian et al. (2015), Kaspi et al. (2014), Repoux et al. (2018), and Molnar and Correia (2019). Boyacı et al. (2017) investigate such a system, in a model that compares 'book in-advance' versus use on-demand configurations using a simulation-based approach on empirical usage data from a station-based one-way carsharing operator in Nice (France). They find that the book in-advance configuration outperforms the on-demand configuration in system robustness and number of requests served. Similarly, Alfian et al. (2015) simulated a reservation-based and an on-demand use one-way carsharing system and show the reservation-based system outperforms the on-demand system when the number of customer increases, and on-demand system is better for real-world application when the fleet size is large enough. Kaspi et al. (2014) propose a parking reservation policy which requires users to declare their destination and the system reserves a parking space for them at their destination, and then apply discrete event simulation and optimisation techniques to compare the parking space reservation policy with the no-reservation policy. In Repoux et al. (2018), the operator accepts a reservation only if a vehicle is available at the origin and parking is available at the destination. Once the reservation is accepted, both (vehicle and space) are reserved for the user. Relocation policies using the reservation information are compared with other relocation mechanisms by simulation. Molnar and Correia (2019) propose a relocation-based reservation enforcement method to FFCS system, which locks a vehicle only a short time before a trip departure. If no available vehicles nearby, the operator relocates a vehicle from a different place. Simulation-based optimisation is used in this study to optimise the performance of the reservation-relocation approach, and the case study demonstrate the proposed approach performs better than the simple vehicle-locking approach.

Other than vehicle allocation mechanisms mentioned above, trip joining and splitting (Barth et al. 2004), secondary market (Le Vine 2014), integrated operator/user-based system rebalancing (Xu et al. 2018), and integrated operator-based vehicle rebalancing and ridesharing (Wen et al. 2017) are also investigated. Detailed reviews of vehicle allocation problem in carsharing can be found in Cepolina and Farina (2012), Jorge and Correia (2013) and Brendel and Kolbe (2017).

## 2.3. Risky-choice

Risky-choice means several possible outcomes are associated with a single choice (Liu and Polak 2014). This choices are common in everyday life, and studies adopting risky-choice analysis vary across many areas, including lottery (Holt and Laury 2002; Masclet et al. 2009), investment (Grable 1997; Schubert et al. 1999), insurance (Outreville 2014; Cicchetti and Dubin 1994), and route choice (de Moraes Ramos et al. 2011; Li and Hensher 2011).

One assumption is individuals choose the option with the highest expected utility, which is the sum of the products of probability and utility over all possible outcomes. This assumption is called expected utility theory (EUT). Combining EUT with random utility theory (Liu and Polak 2014), the utility of option $n$ is (Eq. (1)):

$$U^n = \mathbb{E}\left(v_s^n\right) + \epsilon^n \tag{1}$$

where $U^n$ is the utility of option $n$, $v_s^n$ is the utility of outcome $s$, and $\epsilon^n$ is the unobservable part of the utility function.

An important generalisation of EUT is the incorporation of users' risk-taking behaviour, which can be categorised as risk-aversion, risk-seeking and risk-neutral (Starmer 2000). To be specific, given a gamble having two results with the same expected payoff but different uncertainty, risk-averse individuals prefer the less uncertain result, risk-seeking individuals prefer the more uncertain result, and risk-neutral individuals are indifferent between the two results. Popular nonlinear utility formulations are:

- Negative exponential utility function, also referred to as Constant Average Risk Aversion (CARA; see discussion below): $u(x) = \frac{1 - e^{-\alpha x}}{\alpha}$
- Power utility function, also referred to as Constant Relative Risk Aversion (CRRA; see discussion below): $u(x) = \lambda \frac{x^{1-r}}{1-r}$
- Quadratic utility function: $u(x) = ax - bx^2$

The convexity/concavity of the nonlinear utility transformations indicates users' risk preference, with concave utility functions for risk-averse, convex utility functions for risk-seeking, and linear utility functions for risk-neutral decision makers.

As Liu and Polak (2014) suggested, the corresponding nonlinear utility formulation of option $n$ is (Eq. (2)):

$$U^n = \mathbb{E}\left(g\left(v_s^n, \phi\right)\right) + \epsilon^n \tag{2}$$

where $g\left(v_s^n, \phi\right)$ is the nonlinear transformation of $v_s^n$, and $\phi$ is the additional parameters of the nonlinear transformation.

Arrow (1965) and Pratt (1964) define coefficients of absolute ($A^a$) and relative risk aversion ($A^r$), which can be defined by:

$$A^a = -\frac{u''(x)}{u'(x)} \tag{3}$$

$$A^r = -\frac{x \cdot u''(x)}{u'(x)} \tag{4}$$

and power utility function has constant relative risk aversion (CRRA) and negative exponential utility function has constant absolute risk aversion (CARA).

There are four axioms (completeness, transitivity, independence and continuity) to define rational decision makers under EUT (Von Neumann and Morgenstern 1944). As experimental studies revealed that EUT has systematic violations of its predictions, a large number of non-EUT models are created, with some of the EUT axioms are relaxed. Examples of non-EUT models include subjected expected utility theory, rank-dependent expected utility theory, and prospect utility theory. Detailed review of non-EUT are presented in (Machina 1989).

## 2.4. “Big Five” personality traits

The “Big Five” personality traits (aka “Five-factor model”) is the most widely used taxonomy of personality (Barrick et al. 2001). It collapses personality traits into five standard dimensions, yielding a comprehensive yet parsimonious theoretical framework: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (abbreviated ‘OCEAN’ or ‘CANOE’) (Devaraj et al. 2008). The carsharing literature contains a range of studies that have investigated user attitudes and personality traits (intrinsic preference for driving (Kim et al. 2017c), environmental concern (Kim et al. 2017c; Millard-Ball et al. 2005; Zheng et al. 2009), valuation of car ownership (Kim et al. 2017c; Millard-Ball et al. 2005; Zheng et al. 2009), and privacy-seeking (Kim et al. 2017c)), however to the authors’ knowledge the standard Big Five approach has not previously been employed on this research question.

The Big Five dimensions have been summarized by McCrae and John (1990) as Table 1:

*Table 1 Examples of adjectives, Q-sort items, and questionnaire scales defining the five factors (reproduced from McCrae and John (1990))*

| Factor | | Factor definers | | |
|---|---|---|---|---|
| Name | Number | Adjectives | Q-sort items* | Scales |
| Extraversion (E) | I | Active | Talkative | Warmth |
| | | Assertive | Skilled in play, humour | Gregariousness |
| | | Energetic | Rapid personal tempo | Assertiveness |
| | | Enthusiastic | Facially, gesturally expressive | Activity |
| | | Outgoing | Behaves assertively | Excitement seeking |
| | | Talkative | Gregarious | Positive emotions |
| Agreeableness (A) | II | Appreciative | Not critical, sceptical | Trust |
| | | Forgiving | Behaves in giving way | Straightforwardness |
| | | Generous | Sympathetic, considerable | Altruism |
| | | Kind | Arouse liking | Compliance |
| | | Sympathetic | Warm, compassionate | Modesty |
| | | Trusting | Basically trustful | Tender-mindedness |
| Conscientiousness (C) | III | Efficient | Dependable, responsible | Competence |
| | | Organised | Productive | Order |
| | | Planful | Abel to delay gratification | Dutifulness |
| | | Reliable | Not self-indulgent | Achievement striving |
| | | Responsible | Behaves ethically | Self-discipline |
| | | Thorough | Has high aspiration level | Deliberation |
| Neuroticism (N) | IV | Anxious | Thin-skinned | Anxiety |
| | | Self-pitying | Brittle ego defences | Hostility |
| | | Tense | Self-defeating | Depression |
| | | Touchy | Basically anxious | Self-Consciousness |
| | | Unstable | Concerned with adequacy | Impulsiveness |
| | | Worrying | Fluctuating moods | Vulnerability |
| Openness (O) | V | Artistic | Wide range of interests | Fantasy |
| | | Curious | Introspective | Aesthetics |
| | | Imaginative | Unusual thought process | Feelings |
| | | Insightful | Values intellectual matters | Actions |
| | | Original | Judges in unconventional terms | Ideas |
| | | Wide interests | Aesthetically reactive | Values |

* Q-sort method is used to test reliability and construct validity of questionnaire items at a pretesting stage (see (Nahm et al. 2002) and (McCrae, Costa, and Busch 1986)).

A body of literature exists regarding various techniques to elicit measurements of individuals’ Big Five traits (Gosling et al. 2003; Rammstedt and John 2007; Donnellan et al. 2006), with different approaches of managing the trade-off between information content and time-efficiency; examples are the BFI-44 (Big Five inventory with 44 items to answer), NEO-PI-R (revised Neuroticism-Extraversion-Openness inventory with 240 items to answer), and BFI-10 (Big Five inventory with 10 items to answer, see Rammstedt and John (2007)). In the present study, recognising the high response burden of the stated-choice module of the survey (see next section), we employed BFI-10 as it has a relatively low response burden.

It has been found that the Big Five personality traits correlate with many aspects of human life, such as job performance (Judge et al. 1999; Leutner et al. 2014), social media usage (Ryan and Xenos 2011), new technology adoption (Barnett et al. 2015; Devaraj et al. 2008), risk-taking attitude (Oehler and Wedlich 2018) and driving behaviour (Gadbois and Dugan 2015). Of relevance to FFCS, Neuroticism has been found to negatively associate with perceived usefulness of new technology (see Barnett et al. (2015) and Devaraj et al. (2008)). Risk-averse behaviour has been found to positively correlate with Conscientiousness and Neuroticism, with the opposite for Extraversion (see Oehler and Wedlich (2018)). Agreeableness, Conscientiousness and Openness have been found to positively correlate with environmental engagement (see Milfont and Sibley (2012) and Gifford and Nilsson (2014)). Given that FFCS is a new technological application, and the fact that there is inherent risk of unavailability in the current 'spontaneous' usage model, and that car use impacts emissions and other environmental issues, we hypothesize that these Big Five personality traits may be linked with FFCS usage.

# 3. Survey design and data collection

In this section we first introduce the design of the survey, followed by the data collection process, and the dataset that was generated. The stated-choice survey is composed of three games with increasing complexity as the survey progresses, along with respondents' socio-demographic features, Big Five personality traits, and frequency of usage (all collected upon completion of the main part of the survey).

## 3.1. Design of Games 1 and 2: Existing FFCS service model and Virtual Queuing

The first of the survey's three games (Game 1) presents respondents with a mode choice between FFCS as it operates today and other modes of transport. Game 2 is similar to Game 1, with the difference being that one of the FFCS options is VQ. This information is introduced to respondents at the beginning of Game 2[1]. The VQ option can be either FFCS option A or B. The difference between the VQ option and the other FFCS option is that the VQ option has a non-zero waiting time.

Example game boards for Game 1 and 2 are shown in Figure 1 (top) and Figure 1 (middle), respectively. Respondents were asked to imagine in the beginning of the games that they are planning to shortly leave home to visit a friend, and they need to indicate which transport mode to take. The options include two FFCS options and another mode. The third mode varied between private car, bus or app-based taxi. We blocked the respondents by the third mode according to each respondent's ownership of household vehicles and whether or not they have ever used an app-based taxi service. If a respondent says 'no' to either ownership of household vehicles or experience of using app-based taxi, he or she will not be presented with these two options in the games.

In the design employed for the main fieldwork, each game is composed of six choice situations whose orders are randomised before they are presented to the respondents. The survey was developed through a D-efficient design process (Rose and Bliemer 2009), with priors sourced from the literature

[1] The wording we used to present the VQ information at the beginning of Game 2: *"In the next part of the survey, the Free-Floating Carsharing Service will be a little different from how it works now. You can either use a Free-Floating Carsharing vehicle that is available now, or choose to book one that is currently in use by another customer but will be ready for you in a few minutes. The app shows this to you as…"*

and updated using the results from piloting (n=11) the survey design. The attributes that were used to describe the modes and their levels are listed in Table 2. We did not introduce bespoke constraints to the combinations of driving/riding travel times of different modes presented to respondents. This design strategy could therefore result in a respondent being presented a choice between, say, a "private car" that would incur 30 minutes of travel time and an FFCS vehicle that would incur only 15 minutes. If all automobiles have the same access to the road network this could be a rather large difference between one automobile-based mode and another, however there are plausible reasons that travel times could vary across different auto-based modes. For instance, priority access to managed lanes[2], differential knowledge of road network conditions by an expert (e.g. taxi) driver, or differentials in parking search times would be plausible mechanisms to yield non-trivial differences in travel times for different automobile-based modes. This approach also has the effect of maximising the variation in attribute levels used in model estimation, and hence maximising statistical efficiency.

*Table 2: Attributes and levels*

| **Attributes** | **Game #** | **Option** | **Attribute levels** |
|---|---|---|---|
| Waiting time | 1 and 2 | Bus and app-based taxi | 3, 5, and 10 mins |
| | 2 | FFCS | 0, 3 and 10 mins |
| Waking time | 1 and 2 | FFCS, private car and bus | 3, 5, and 10 mins |
| | 3 | Use on-demand | 3, 5, and 10 mins |
| In-vehicle travel time | 1 and 2 | FFCS, private car and app-based taxi | 15, 20 and 30 mins |
| | 1 and 2 | Bus | 20, 30 and 45 mins |
| Price | 1 and 2 | FFCS and private vehicle | £5, £8 and £10 |
| | 3 | Use on-demand | £5, £8 and £10 |
| | 1 and 2 | Bus | £1.50, £2.40 and £3.30 |
| | 1 and 2 | App-based taxi | £8, £10 and £15 |
| Walking time (lowest bound) | 3 | Reserve in-advance | 1 min |
| Walking time (most likely value) | 3 | Reserve in-advance | 3, 5, and 8 mins |
| Walking time (highest bound) | 3 | Reserve in-advance | 10, 12, and 15 mins |
| Price (lowest bound) | 3 | Reserve in-advance | £1 |
| Price (most likely value) | 3 | Reserve in-advance | £3, £5, and £8 |
| Price (highest bound) | 3 | Reserve in-advance | £10, £12, and £15 |

We pilot-tested an early version of the survey in which respondents were presented with different activity purposes in each choice situation, with purposes intended to convey 'strict' time constraints (e.g. a doctor's appointment) versus less-rigid scheduling requirements (e.g. visiting a friend). Feedback during piloting indicated that varying activity purpose across replications introduced a magnitude of additional response burden that we decided was not justified by our research objectives. We therefore removed activity purpose from the design of the SC replications for the main fieldwork, and hence leave the issue of establishing the influence of different scheduling constraints for different activity types as a topic for future research.

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[2] E.g. taxis are allowed in bus lanes in London https://tfl.gov.uk/modes/driving/red-routes/rules-of-red-routes/bus-lanes

| | Free-Floating Carsharing vehicle A | Free-Floating Carsharing vehicle B | Bus option |
|---|---|---|---|
| Waiting time | No wait | No wait | 5 mins |
| Walking time | 10 mins | 3 mins | 10 mins |
| Driving/Riding time | 15 mins | 15 mins | 30 mins |
| Price | £5 | £10 | £3.3 |

| | Free-Floating Carsharing vehicle A | Free-Floating Carsharing vehicle B | Bus option |
|---|---|---|---|
| Which one would you choose? | | | |

| | Free-Floating Carsharing vehicle A | Free-Floating Carsharing vehicle B | App-based taxi |
|---|---|---|---|
| Waiting time | 3 mins | No wait | 5 mins |
| Walking time | 3 mins | 10 mins | No walk |
| Driving/Riding time | 15 mins | 30 mins | 20 mins |
| Price | £10 | £5 | £15 |

| | Free-Floating Carsharing vehicle A | Free-Floating Carsharing vehicle B | App-based taxi |
|---|---|---|---|
| Which one would you choose? | | | |

| | Reserve a Free-Floating Carsharing vehicle in advance | Wait and then use a Free-Floating Carsharing vehicle on demand |
|---|---|---|
| Walking time | 5 mins | Walking could be as little as ***1 min*** or as much as ***15 mins***, with ***3 mins*** the most likely walking time |
| Price | £10 | Price could be as little as ***£1*** or as much as ***£10***, with ***£8*** the most likely price |

| | Reserve a Free-Floating Carsharing vehicle in advance | Wait and then use a Free-Floating Carsharing vehicle on demand |
|---|---|---|
| Which one would you choose? | | |

*Figure 1: Example of stated-choice situation for Game 1 (top), Game 2 (middle), and Game 3 (bottom)*

## 3.2. Design of Game 3: Guaranteed Advance Reservation

Game 3 is the most complex of the three games; respondents are tasked with selecting between reserving a vehicle for a journey to begin in several hours into the future or to wait and then book on demand as the journey's planned departure time approaches.

As in Games 1 and 2, respondents are asked to imagine that they will need to visit a friend, however in Game 3 they are also asked to imagine that they plan to leave several hours later to meet their friend. Unlike in Games 1 and 2, respondents choose only between the existing (spontaneous usage) and GAR service model; no other modes are presented. Additionally, driving time for either options is fixed to be 20 minutes. Figure 1 (bottom) presents an example Game 3 game board. Both GAR and spontaneous usage are described by combinations of walking time and price. As in Game 1 and 2, Game 3 is constructed through D-efficient design. Each respondent is presented with six replications with randomised order. We did not block respondents in this game as Game 3 does not contain the third alternative (a non-FFCS mode of travel, tailored for each respondent), as in the case of Games 1 and 2. The attributes that were used to describe the two services and their levels are listed in Table 2.

Presenting uncertain attributes in SC surveys in ways that are readily understandable by respondents presents unique challenges (Bates et al. 2001). A variety of techniques have been developed to convey probability distributions, including the 'clock-face' in Bates et al. (2001), the 'two mass point' distribution in Latinopoulos et al. (2017), the ‘three mass point’ distribution in Li et al. (2016) and Li et al. (2010), the ‘range of variation’ in Li et al. (2016) and Li et al. (2010), and the ‘list of possible travel times’ in Small et al. (1999). In the context of FFCS, the expected range of uncertainty in price and walking time are relatively small (measured in small number of minutes or GBP), as accessibility to FFCS vehicles will increase with the square of walking distance, which will tend to reduce the occurrence of a very large walking time being required to access the nearest vehicle, and it is unlikely for the FFCS to charge users with a large amount of money for a journey. This is a quite different phenomenon than, for instance, the distribution of travel times on a freeway (another widely studied context of attribute uncertainty), in which typical day-to-day variation is moderate but with a small probability of serious disruptions leading to much larger travel times. Therefore, we choose to present uncertainty of price and walking time to respondents in the form of triangular distributions via a definite lower bound (because neither price nor walking time can be negative), the modal value of the distribution (presented to respondents as the “most likely” value), and a definite upper bound (i.e. neither of these quantities can be arbitrarily large) (see Figure 1 (bottom)).

We considered including the possibility of vehicle unavailability as a third component of uncertainty associated with the spontaneous usage alternative, however we decided against this for two reasons. First, in the context of a free-floating shared fleet, there is no clear distinction between service unavailability and long walk times to the nearest vehicle, with the exception of the limiting case of all vehicles in the shared fleet being currently used by other users and hence unavailable to the user making a request-for-service. Second, prior SC studies of choice-under-uncertainty in the context of mode choice ask respondents to consider a single dimension of uncertainty in each stated-choice replication. We decided that it was therefore prudent to introduce one additional dimension of uncertainty in this study, rather than two. Adding a third dimension of uncertainty (alongside the walking-time and price dimensions) would introduce a more demanding requirement for simultaneous information processing by respondents; we decided to leave the issues raised by the inclusion of additional dimensions of uncertainty as an issue for future research.

## 3.3. Data collection and socio-demographic features

The survey was administered to a population of approximately 7,000 existing users of the DriveNow FFCS service in London in January 2018. 453 responses were received, with 289 complete responses (for a full-completion response rate of 4%). Respondents were presented an incentive of being entered into a drawing for a £100 Amazon voucher. A summary of the sample socio-demographics is shown in Table 3, along with a comparison of the socio-demographic features of the sample with London adults at large (sourced from the 2015 National Travel Survey (NTS) dataset). Males, young adults, employed, mid- to high-income, and zero household vehicle households are over-represented in our dataset. These features are consistent with the literature on carsharing users’ socio-demographic characteristics (Kopp et al. 2015; Burkhardt and Millard-Ball 2006; Carplus 2017).

*Table 3: Socio-demographics of the sample (n=289) and 2015 NTS (London adults only, n=2286)*

| Items | | Distribution | Distribution (from NTS 2015) |
|---|---|---|---|
| Gender | Male | 77.2% | 48.2% |
| | Female | 21.1% | 51.8% |
| | Prefer not to answer | 1.7% | |
| Age | 20-29 | 21.5% | 16.9% |
| | 30-39 | 43.6% | 20.5% |
| | 40-49 | 24.2% | 17.9% |
| | 50-59 | 9.0% | 15.7% |
| | 60-69 | 1.0% | 23.2% |
| | Prefer not to answer | 0.7% | |
| Place of residence | Inner London | 66.4% (fare zones 1 and 2) | 39.5% |
| | Outer London | 31.5% | 60.5% |
| | Outside London | 2.1% | N/A |
| Employment status | Full-time | 81.0% | 50.4% |
| | Part-time | 6.2% | 12.7% |
| | Seeking work | 1.0% | 2.4% |
| | Retired | 0.7% | 19.9% |
| | Student | 2.8% | 6.2% |
| | Other | 6.9% | 8.5% |
| | Prefer not to answer | 1.4% | |
| Income | < £5,000 | 1.0% | 4.2% |
| | £5,000 - £24,999 | 12.8% | 30.1% |
| | £25,000 - £49,999 | 33.6% | 25.6% |
| | £50,000 - £74,999 | 17.0% | 18.7% |
| | > £75,000 | 26.3% | 21.3% |
| | Prefer not to answer | 9.3% | |
| Living with partner | Yes | 63.7% | 59.5% |
| | No | 30.8% | 40.5% |
| | Prefer not to answer | 5.5% | |
| # of other adults living with | 0 | 58.8% | 53.5% |
| | 1 | 20.1% | 14.3% |
| | 2+ | 17.3% | 32.2% |
| | Prefer not to answer | 3.8% | |
| # of children living with | 0 | 64.4% | 65.8% |
| | 1 | 13.5% | 16.1% |
| | 2 | 14.5% | 12.7% |
| | 3+ | 3.5% | 5.4% |
| | Prefer not to answer | 4.2% | |
| # of vehicles in the household | 0 | 60.9% | 29.4% |
| | 1 | 30.1% | 45.1% |
| | 2+ | 6.6% | 25.5% |
| | Prefer not to answer | 2.4% | |
| Frequency of using FFCS (only for CS members) | 3 or more times a week | 9.7% | 2.9% |
| | Once or twice a week | 17.6% | 0.0% |
| | Less than that but more than twice a month | 17.0% | 0.0% |
| | Once or twice a month | 24.2% | 2.9% |
| | Less than that but more than twice a year | 24.6% | 38.2% |
| | Once or twice a year | 6.6% | 32.4% |
| | Less than that or never | 0.0% | 23.5% |
| | Prefer not to answer | 0.3% | |
| Big Five personality traits[3] (See Table SM2 in the Supplementary Material) | Extraversion | 3.52 (0.95) | N/A |
| | Agreeableness | 3.58 (0.88) | N/A |
| | Conscientiousness | 3.95 (0.84) | N/A |
| | Neuroticism | 2.20 (1.03) | N/A |
| | Openness | 3.61 (0.87) | N/A |

[3] See Table SM2 of the Supplementary Material for question wording and procedure for converting between responses and each of the Big Five personality characteristics.

# 4. Modelling framework

We introduce the modelling framework that is used to model the risky-choice behaviour of respondents in this section. The modelling framework is developed based on random utility theory and expected utility theory (see Section 2.3). We introduce first the linear and then the nonlinear utility forms, with the latter (but not the former) considering respondents' risk-taking behaviour. Notation is summarised in Table 4.

*Table 4: Table of Notation*

| | |
|---|---|
| $n$ | Index for options |
| $a,u$ | Indices for attribute- or utility-level transformation |
| $s$ | Index for a possible outcome of an option |
| $U$ | Utility |
| $v$ | The observable part of the utility |
| $\epsilon$ | The unobservable part of the utility |
| $wk$ | Walking time |
| $p$ | Price |
| $ASC$ | Alternative specific constant |
| $\beta$ | Users' sensitivity to attributes |
| $\alpha$ | Nonlinear transformation parameter for CARA |
| $b$ | Nonlinear transformation parameter for quadratic transformation |
| $\gamma$ | Nonlinear transformation parameter for CRRA |
| $g(\cdot)$ | A transformation function (can be either linear or nonlinear) |

For the first two games without risky-choices, the utility of options can be described by classic random utility theory. For the use on-demand option in Game 3 with two dimensions of uncertain attributes, we will need the modelling techniques introduced in Section 2.3.

As we have multiple dimensions of uncertainty (two in our specific case study), a decision must be made about the level at which the utility function is transformed: we can either first compute the expected value of each uncertain attribute independently of one another and then sum them (which we henceforth refer to as the "attribute-level" approach), or we can first compute the utility associated with each outcome and then compute the aggregate expected value (the "utility-level" approach). These two approaches have been employed in earlier studies that have considered a single dimension of uncertainty, with Hu et al. (2012) and Hensher et al. (2011) as examples of the attribute-level approach and Liu and Polak (2014) as an example of the utility-level approach. These two ways of describing the utility are formalised in Eq. (5)-(6) (for our analysis containing two dimensions of uncertainty):

$$U_a^n = ASC_a^n + \beta_{wk,a} \cdot \mathbb{E}\big(g(wk_s^n)\big) + \beta_{p,a} \cdot \mathbb{E}\big(g(p_s^n)\big) + \epsilon^n \tag{5}$$

$$U_u^n = ASC_u^n + \mathbb{E}\big(g(v_s^n)\big) + \epsilon^n \tag{6}$$

In this study, we assume $v_s^n$ is a linear function of $wk_s^n$ and $p_s^n$ (Eq. (7)):

$$v_s^n = \beta_{wk,u} \cdot wk_s^n + \beta_{p,u} \cdot p_s^n \tag{7}$$

If we assume $g(\cdot)$ equals to the variable inside the bracket, which implies individuals are all risk neutral, we will get:

$$U_a^n = U_u^n = ASC + \beta_{wk} \cdot \mathbb{E}\big(wk_s^n\big) + \beta_p \cdot \mathbb{E}\big(p_s^n\big) + \epsilon^n \tag{8}$$

To take users' risk-taking attitudes into account, we introduce additional parameters and describe $g(\cdot)$ in Eq. (5) and Eq. (6) as nonlinear functions. We introduced three nonlinear utility formulations in Section 2.3, and the attribute-level utility functions are Eq. (9)-(11):

$$U_{a,CARA}^{n} = ASC_{a,CARA}^{n} + \beta_{wk,a} \cdot \mathbb{E}\left(\frac{1 - e^{-\alpha_{wk} \cdot wk_s^n}}{\alpha_{wk}}\right) + \beta_{p,a} \cdot \mathbb{E}\left(\frac{1 - e^{-\alpha_p \cdot p_s^n}}{\alpha_p}\right) + \epsilon^n \tag{9}$$

$$U_{a,CRRA}^{n} = ASC_{a,CRRA}^{n} + \beta_{wk,a} \cdot \mathbb{E}\left(\frac{\left(wk_s^n\right)^{1 - r_{wk}}}{1 - r_{wk}}\right) + \beta_{p,a} \cdot \mathbb{E}\left(\frac{\left(p_s^n\right)^{1 - r_p}}{1 - r_p}\right) + \epsilon^n \tag{10}$$

$$U_{a,quad}^{n} = ASC_{a,quad}^{n} + \beta_{wk,a}\mathbb{E}\left(wk_s^n\right) - b_{wk,a}\mathbb{E}\left(wk_s^n\right)^2 + \beta_{p,a}\mathbb{E}\left(p_s^n\right) - b_{p,a}\mathbb{E}\left(p_s^n\right)^2 + \epsilon^n \tag{11}$$

Using Eq. (7) to describe $v_s^n$, the utility-level functions of the four nonlinear utility formulations are (Eq. (12)-(14)):

$$U_{u,CARA}^{n} = ASC_{u,CARA}^{n} - \mathbb{E}\left(\frac{1 - e^{-\alpha\left(\beta_{wk,u} \cdot wk_s^n + \beta_{p,u} \cdot p_s^n\right)}}{\alpha}\right) + \epsilon^n \tag{12}$$

$$U_{u,CRRA}^{n} = ASC_{u,CRRA}^{n} - \mathbb{E}\left(\frac{\left(\beta_{wk,u} \cdot wk_s^n + \beta_{p,u} \cdot p_s^n\right)^{1 - r}}{1 - r}\right) + \epsilon^n \tag{13}$$

$$U_{u,quad}^{n} = ASC_{u,quad}^{n} - \mathbb{E}\left(\left(\beta_{wk,u} \cdot wk_s^n + \beta_{p,u} \cdot p_s^n\right) - b \cdot \left(\beta_{wk,u} \cdot wk_s^n + \beta_{p,u} \cdot p_s^n\right)^2\right) + \epsilon^n \tag{14}$$

By comparing Eq. (9)-(11) and Eq. (12)-(14), it can be seen that the attribute- and utility-level functions are not identical; this holds for the CARA, CRRA, and quadratic forms. Even in the limiting case of a single dimension of uncertainty, the two approaches to transformation (attribute-level and utility-level) are not mathematically identical.

# 5. Modelling approach and results

In this section, we present results from analysing the choices made by the respondents in the three SC games. The first two games are modelled by multinomial logit models (MNL), based on random utility theory (RUT). For Game 3, we model users' behaviour under the uncertain walking time and price in the SC survey. We present the results with and without the consideration of users' risk-taking behaviour. In all three games, we include a panel effect parameter, which captures correlation across multiple responses from the same individual (Louviere et al. 2000). Respondents that selected "prefer not to answer" for any socio-demographic or attitudinal question were excluded from the analyses shown in Table 5-Table 11, yielding an effective sample size of n=232 for these analyses.

In the discussion that follows, we employ speculative language ("could", "may", etc.) to discuss possible explanations for findings that the results suggest but which cannot be unambiguously concluded by statistical analysis alone.

## 5.1. Mode choice analyses (FFCS vs Bus/Private Car/App-based taxi)

Table 5 presents the estimation of the mode choice situations for the existing FFCS service. Model #1-1 shows that the design variables of cost and various time components (walking time, waiting time, and in-vehicle time) all have the expected sign and are highly statistically significant.

Respondents are most averse to walking time, followed by waiting time and in-vehicle time. The panel-effect parameter is insignificant.

Model #1-2 adds demographic effects, and Model #1-3 also incorporates the Big Five personality traits. Effects with $p>0.15$ are excluded; the in-text discussion that follows is limited to effects significant at the usual $p<0.05$ level. We find that the presence of children in the household is negatively associated with FFCS usage, and vice versa for owning a household automobile (which may indicate unobserved propensity for automobile usage, whether FFCS or private car). Frequency of real-world FFCS usage is also strongly associated with choosing to use FFCS in Game 1 (as opposed to choosing the other mode options).

In Model #1-3, we find that respondents who score highly on Extraversion and Openness are more likely (ceteris paribus) to choose FFCS, whereas Agreeableness is associated with lower likelihood of using FFCS. These findings regarding Openness and Extraversion align with our a priori expectations (see discussion in Section 2.4); for instance, the typical result in the literature is that Extraversion is positively linked with risk-taking behaviour, which is manifest in the volatile fleet-availability characteristics of FFCS as operated today. The negative association between Agreeableness and FFCS usage is not in line with our intuition, as we had expected a positive relationship (because Agreeableness has been previously found to be linked with concern for the environment, see Milfont and Sibley (2012) and Gifford and Nilsson (2014)).

To investigate this result further, we compared the proportion of choices to use FFCS (versus other modes) for respondents with high and low scores on the Agreeableness dimension (Table 6). We found that respondents with high Agreeableness are more likely to choose Bus than FFCS or app-based taxi, and more likely to choose all of these than private car. The results in Table 6 are consistent with a possible interpretation that public transport is in general seen to be most environmentally friendly, and private car use the least (with FFCS and app-based taxi between these two extremes).

## 5.2. Modelling results of the mode choice games for Virtual Queuing

Table 7 presents results relating to willingness-to-pay (WTP) for VQ. The results without the impact of socio-demographic features and Big Five personality traits suggest that respondents are on average not willing to pay for VQ, with a negative calculated WTP of £0.76 (-0.281 / 0.368 = -£0.76 (±£0.25)). Time spent during VQ (value of time £23.32 ± £4.47 per hour) was found to be more burdensome than time waiting for bus or app-based taxi (value of time £20.05 ± £4.21 per hour). One possibility for this distaste for waiting for a FFCS vehicle is that customers are accustomed to waiting a short period of time for buses and app-based taxi services, whereas FFCS vehicles are currently available without waiting.

Mishra et al. (2015) report that gender, income, the presence of children, and frequency of using public transport and active commute modes impact respondents' attitude towards waiting for public transport. In Model #2-2, we find no significant (or close to significant) relationships between socio-demographic features and propensity to use VQ in a FFCS system. Model #2-3, however, shows significant associations with two of the Big Five personality traits: Extraversion is positively linked with using VQ, and vice versa for Agreeableness. A possible interpretation with respect to Extraversion is that the 'active' and 'energetic' aspects of Extraversion (see Section 2.4 and McCrae and John (1990)) are part of the reason for VQ being attractive to people scoring high on this dimension. Likewise, the 'forgiving' and 'trusting' aspects of Agreeableness appear to intuitively be possible explanations for people scoring high on Agreeableness being less likely to choose VQ, as people characterizable as 'trusting' may be less inclined to choose the VQ mechanism to manage their access to the FFCS service, and instead gamble that the uncontrollable spatial distribution of vehicles may happen to result in a vehicle being available when and where they desire.

*Table 5: Estimation of game 1 (existing services)*

| **Attribute** | | **Without socio-demographics** | | **With socio-demographics** | | **With socio-demographics & Big Five traits** | |
|---|---|---|---|---|---|---|---|
| | | **Model #1-1** | | **Model #1-2** | | **Model #1-3** | |
| | | Value | p-value | Value | p-value | Value | p-value |
| Alternative specific constant | Car | 0.119 | 0.39 | 0.641 | 0.01 | 0.702 | 0.23 |
| | Bus | -0.0930 | 0.65 | 0.0934 | 0.67 | 0.0713 | 0.90 |
| | App-based taxi | -0.0556 | 0.77 | 0.217 | 0.33 | 0.319 | 0.59 |
| | FFCS | 0 (fixed) | | 0 (fixed) | | 0 (fixed) | |
| Panel Effect | | 0.0799 | 0.86 | 0.00905 | 0.99 | 0.00280 | 0.99 |
| Time (minutes) | Walking time (for FFCS, car and bus) | -0.168 | <0.01 | -0.171 | <0.01 | -0.173 | <0.01 |
| | Waiting time (for bus and app-based taxi) | -0.135 | <0.01 | -0.136 | <0.01 | -0.137 | <0.01 |
| | In-vehicle time | -0.102 | <0.01 | -0.103 | <0.01 | -0.105 | <0.01 |
| Price | GBP per journey | -0.350 | <0.01 | -0.355 | <0.01 | -0.361 | <0.01 |
| Age | 20-29 | | | * | | -0.351 | 0.06 |
| | 30-39 | | | 0 (fixed) | | 0 (fixed) | |
| | 40-49 | | | * | | * | |
| | 50+ | | | * | | * | |
| Gender | Female | | | * | | * | |
| Employment status | Unemployed | | | * | | * | |
| Income | 1 for income higher than £50k/year | | | * | | -0.232 | 0.13 |
| # of other members in the family | Living with partner | | | * | | * | |
| | Living with adults other than partner | | | * | | * | |
| | Having children | | | -0.460 | <0.01 | -0.493 | <0.01 |
| Home location | Outer or Outside London | | | 0.248 | 0.10 | 0.263 | 0.09 |
| Presence of at least one household vehicles | 1 for having at least one private vehicle | | | 0.424 | 0.04 | 0.513 | 0.02 |
| Frequency of using FFCS | 1 for using FFCS more than twice a month | | | 0.482 | <0.01 | 0.499 | <0.01 |
| Big Five traits | Openness | | | | | 0.191 | 0.02 |
| | Agreeableness | | | | | -0.179 | 0.03 |
| | Extraversion | | | | | 0.202 | 0.01 |
| | Conscientiousness | | | | | -0.136 | 0.13 |
| | Neuroticism | | | | | * | |
| $\rho^2$ | | 0.191 | | 0.200 | | 0.207 | |
| Adjusted $\rho^2$ | | 0.186 | | 0.192 | | 0.195 | |

* All parameters with initial significance level p>0.15 have been removed prior to performing these runs.

*Table 6: Percentage of respondents choosing FFCS for each choice situation*

| | % of respondents choosing FFCS | |
|---|---|---|
| Choice situation | Agreeableness<=3 | Agreeableness>3 |
| FFCS and private car | 57% | 68% |
| FFCS and bus | 74% | 61% |
| FFCS and app-based taxi | 74% | 72% |

## 5.3. Modelling results of the reservation game (without risk-taking behaviour)

Table 8 presents results where respondents choose between the current spontaneous-usage FFCS service model and the prospective GAR model.

Model #3-1 shows that users are willing to pay approximately £0.54 per journey for the GAR option (via division of the relevant parameters: 0.310 / 0.577 = £0.54 (± £0.12)). This result should be viewed as applying solely within the context of this survey, in which respondents were presented with an activity of visiting friends. Further research will be required to establish how this value may vary across different journey purposes with different scheduling requirements (e.g. users would be expected to have higher WTP for activity types where on-time arrival is particularly important).

The only Big Five characteristic that correlates with the choice of using GAR is Conscientiousness, with the high scoring respondents being more likely to book in-advance. This is an intuitive result, as McCrae and John (1990) demonstrates that Conscientiousness is associated with advance planning (described as ‘planful’) and being ‘organised’ (see listing in Section 2.4).

Model #3-3 suggests that age has a significant influence: Respondents in their 30s are more likely than other age groups (both younger and older) to choose the GAR option. Frequent FFCS usage is also found to negatively associate with choosing to book in-advance; one possibility is that frequent FFCS users have unobserved personal characteristics that render them less sensitive to service availability, and a second is that heavy FFCS users may have developed mechanisms to manage service volatility and hence see less of a need to pay a premium for GAR.

*Table 7: Estimation of game 2 (VQ)*

| Attribute | | Without socio-demographics | | With socio-demographics | With socio-demographics & Big Five traits | |
|---|---|---|---|---|---|---|
| | | **Model #2-1** | | **Model #2-2** | **Model #2-3** | |
| | | Value | p-value | | Value | p-value |
| Alternative specific constant | Car | 0.518 | <0.01 | All socio-demographic features are not significant | 0.514 | <0.01 |
| | Bus | -0.326 | 0.10 | | -0.329 | 0.10 |
| | App-based taxi | -0.380 | 0.08 | | -0.372 | 0.09 |
| | Virtual Queueing | -0.281 | <0.01 | | -0.101 | 0.67 |
| | FFCS | 0 (fixed) | | | 0 (fixed) | |
| Panel effect | Virtual Queueing | 0.559 | <0.01 | | 0.508 | <0.01 |
| Time (minutes) | Walking time (for FFCS, car and bus) | -0.179 | <0.01 | | -0.179 | <0.01 |
| | Waiting time (for bus and app-based taxi) | -0.123 | <0.01 | | -0.123 | <0.01 |
| | Waiting time (for FFCS) | -0.143 | <0.01 | | -0.141 | <0.01 |
| | In-vehicle time | -0.117 | <0.01 | | -0.117 | <0.01 |
| Price | GBP per journey | -0.368 | <0.01 | | -0.367 | <0.01 |
| Age | 20-29 | | | | * | |
| | 30-39 | | | | | |
| | 40-49 | | | | * | |
| | 50+ | | | | * | |
| Gender | Female | | | | * | |
| Employment status | Unemployed | | | | * | |
| Income | 1 for income higher than £50k/year | | | | * | |
| # of other members in the family | Living with partner | | | | * | |
| | Living with adults other than partner | | | | * | |
| | Having kids | | | | * | |
| Home location | Outer or outside London | | | | * | |
| Presence of at least one household vehicles | 1 for having at least one private vehicle | | | | * | |
| Frequency of using FFCS | 1 for using FFCS more than twice a month | | | | * | |
| Big Five traits | Openness | | | | * | |
| | Agreeableness | | | | -0.243 | 0.01 |
| | Extraversion | | | | 0.142 | 0.09 |
| | Conscientiousness | | | | * | |
| | Neuroticism | | | | * | |
| $\rho^2$ | | 0.208 | | | 0.212 | |
| Adjusted $\rho^2$ | | 0.202 | | | 0.204 | |

*Table 8: Estimation of game 3 (GAR)*

| Attribute | | Without socio-demographics | | With socio-demographics | | With socio-demographics and Big Five traits | |
|---|---|---|---|---|---|---|---|
| | | **Model #3-1** | | **Model #3-2** | | **Model #3-3** | |
| | | Value | p-value | Value | p-value | Value | p-value |
| Alternative specific constant | GAR | 0.310 | <0.01 | 0.446 | <0.01 | 0.0292 | 0.92 |
| | Use on-demand | 0 (fixed) | | 0 (fixed) | | 0 (fixed) | |
| Panel effect | Book in-advance | -1.43 | <0.01 | 1.39 | <0.01 | 1.36 | <0.01 |
| Time (minutes) | Walking time | -0.252 | <0.01 | -0.252 | <0.01 | -0.252 | <0.01 |
| Price | GBP per journey | -0.577 | <0.01 | -0.577 | <0.01 | -0.577 | <0.01 |
| Age | 20-29 | | | -0.586 | 0.05 | -0.733 | 0.02 |
| | 30-39 | | | 0 (fixed) | | 0 (fixed) | |
| | 40-49 | | | -0.421 | 0.14 | -0.562 | 0.05 |
| | 50+ | | | * | | -0.638 | 0.12 |
| Gender | Female | | | * | | * | |
| Employment status | Unemployed | | | * | | * | |
| Income | 1 for income higher than £50k/year | | | * | | * | |
| # of other members in the family | Living with partner | | | * | | * | |
| | Living with adults other than partner | | | 0.424 | 0.08 | 0.473 | 0.05 |
| | Having kids | | | * | | * | |
| Home location | Outer or outside London | | | * | | * | |
| Presence of at least one household vehicles | 1 for having at least one private vehicle | | | * | | * | |
| Frequency of using FFCS | 1 for using FFCS more than twice a month | | | -0.445 | 0.06 | -0.459 | 0.05 |
| Big Five traits | Openness | | | | | * | |
| | Agreeableness | | | | | * | |
| | Extraversion | | | | | * | |
| | Conscientiousness | | | | | 0.240 | 0.08 |
| | Neuroticism | | | | | * | |
| $\rho^2$ | | 0.215 | | 0.221 | | 0.222 | |
| Adjusted $\rho^2$ | | 0.211 | | 0.211 | | 0.212 | |

## 5.4. Modelling results of the reservation game (risk-taking behaviour)

The modelling results of this section are based on the specific attribute values for the triangular distributions of walking time and price that we employed in this survey (see Table 2). There is therefore a risk that the results are idiosyncratic to the small number of specific attribute values that we presented to respondents. Further evidence from additional empirical data collection efforts, ideally utilising both other types of statistical distributions as well as triangular distributions with different parameters, will be required to determine whether our findings on this point are due to the specific survey-design choices we made.

Table 9 presents the results of the three formulations where the uncertain attributes are transformed in the attribute level. Comparing with the results without considering the risk-taking behaviour in Section 5.3, introducing risk-taking behaviour increases overall goodness-of-fit (as measured by adjusted $\rho^2$, which penalises the addition of parameters that add little explanatory power). Goodness-of-fit of the three non-linear utility formulations are similar; the quadratic approach performs marginally better than CARA and CRRA. The ASCs in all three models are significant and positive, which is consistent with the results of the linear utility function form (Section 5.3).

As for the two dimensions of uncertainty, we plot the nonlinear utility for price and walking time in Figure 2. For all three models, the utility for price curves are convex and utility for walking curves are concave (the three walking time curves are very close to each other). Especially, the curvature for price are much greater than walking, and in all three models the parameters for walking are not very significant. These results suggest a strong and significant risk-seeking for price and slight and less significant risk-aversion for walking.

The strong risk-seeking for price and weak risk-averse behaviour for walking time is different from our expectation, as we assume positive willingness-to-pay for GAR implies risk-aversion. One possible explanation is the price of FFCS journeys being regarded as a 'loss' from a user's perspective; risk-seeking in price would therefore be consistent with typical empirical observations; for instance, Kahneman and Tversky (1979) observe that *"risk-seeking in choices between negative prospects was noted as early as Markowitz (1952)"*.

A second possible explanation is that respondents choose GAR for other features of the service aside from a guaranteed price and walking time, such as guaranteed access to the vehicle when desired. We investigated this hypothesis using the utility-level nonlinear formulations in which a single risk-seeking/aversion parameter is estimated. Results are presented in Table 10. As with the attribute-level results, the quadratic utility model has the best goodness-of-fit. The risk-taking parameters are significant in all three models.

Figure 3 shows the shape of the utility-level nonlinear transformations (using the results shown in Table 10). The convexity of each of the three curves indicates that all three model forms find risk-seeking behaviour with respect to the (combined) two dimensions of uncertainty (in all three cases alongside the positive alternative specific constants for GAR reported in Table 10). The result that respondents are risk-seeking to the combined utility components of time and cost tends to support the possible interpretation that preference for GAR could be due, at least in part, to other aspects of GAR than the a priori lock-in of walking time and cost.

For the attribute-level utility results, the nonlinear transformation of walking time and price makes the value of time (VoT, computed by $\frac{dU/dwk}{dU/dp}$) vary at different attribute values. Table 11 shows the VoT of each replication based on the distribution of walking time and price of each replication. As the calculations of VoT take into account the full extents of their distributions, the shape of the nonlinear price and walking time curves influence the computed VoT values. For example, Replication #6 has a large VoT calculated values for CARA (£ 51.96/hour) and CRRA (£37.12/hour), and the small value for the Quadratic form (£3.31/hour). The reason is that Replication #6 has the widest possible distributions of walking time and price distributions (wider than the other 5 replications). For CARA and CRRA, the curves for price become quite flat near the £15/journey upper bound, whereas for the Quadratic form the curve for price has a positive slope (see Figure 2).

The average VoTs of all six replications are compared with the VoT computed from the linear utility function. The VoT computed from the linear utility function is £26.20 per hour (0.252/0.577*60=26.20 (±3.37), see Section 5.3) at all combinations of time and cost values, which is nearer to the mean VoT estimates of CARA (£27.97) and CRRA (£22.92) than the comparable result for the quadratic form (£10.56). The VoTs of the three utility-level transformations (£23.02, £26.41, and £20.84) are all close to the £26.02 obtained from the linear utility function.

*Table 9: Estimation of game 3 (attribute level)*

| Attribute | | CARA | | CRRA | | Quadratic utility | |
|---|---|---|---|---|---|---|---|
| | | Model #3-4 | | Model #3-5 | | Model #3-6 | |
| | | Value | p-value | Value | p-value | Value | p-value |
| Alternative specific constant | GAR | 0.553 | <0.01 | 0.623 | <0.01 | 0.505 | <0.01 |
| | Use on-demand | 0 (fixed) | | 0 (fixed) | | 0 (fixed) | |
| Panel effect | Book in-advance | -1.50 | <0.01 | -1.51 | <0.01 | -1.51 | <0.01 |
| $\beta_{wk,a}$ | | -0.0843 | 0.14 | -0.0306 | 0.45 | 0.0374 | 0.82 |
| $\beta_{p,a}$ | | -6.47 | 0.02 | -23.8 | 0.05 | -2.25 | <0.01 |
| $\alpha^{wk}$ | | -0.133 | 0.16 | | | | |
| $\alpha^{p}$ | | 0.355 | <0.01 | | | | |
| $r^{wk}$ | | | | -1.06 | 0.12 | | |
| $r^{p}$ | | | | 1.96 | <0.01 | | |
| $b_{wk,a}$ | | | | | | 0.0170 | 0.18 |
| $b_{p,a}$ | | | | | | -0.115 | <0.01 |
| $\rho^2$ | | 0.233 | | 0.233 | | 0.235 | |
| Adjusted $\rho^2$ | | 0.226 | | 0.227 | | 0.228 | |

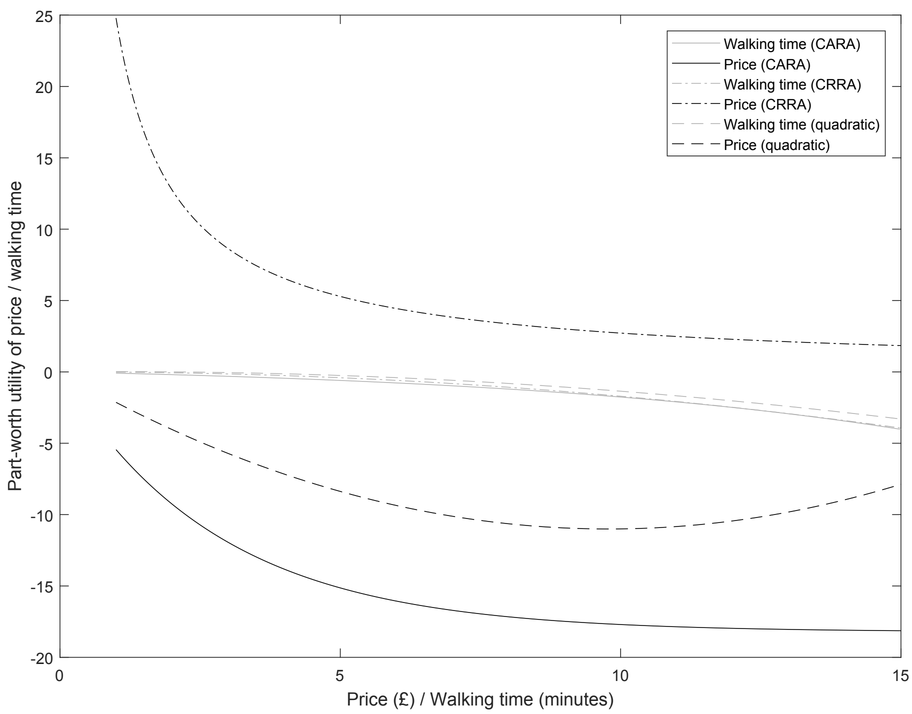


*Figure 2 Nonlinear price and walking time curves, for attribute-level form*

*Table 10: Estimation of game 3 (utility level)*

| Attribute | | CARA | | CRRA | | Quadratic utility | |
|---|---|---|---|---|---|---|---|
| | | Model #3-7 | | Model #3-8 | | Model #3-9 | |
| | | Value | p-value | Value | p-value | Value | p-value |
| Alternative specific constant | GAR | 0.501 | <0.01 | 0.335 | <0.01 | 0.535 | <0.01 |
| | Use on-demand | 0 (fixed) | | 0 (fixed) | | 0 (fixed) | |
| Panel effect | Book in-advance | -1.51 | <0.01 | -1.44 | <0.01 | -1.51 | <0.01 |
| $\beta_{wk,u}$ | | 2.67 | 0.01 | 0.420 | <0.01 | 0.820 | <0.01 |
| $\beta_{p,u}$ | | 6.96 | 0.01 | 0.954 | <0.01 | 2.36 | <0.01 |
| $\alpha$ | | 0.0398 | <0.01 | | | | |
| $r$ | | | | 0.226 | 0.02 | | |
| $b$ | | | | | | 0.0173 | <0.01 |
| $\rho^2$ | | 0.236 | | 0.217 | | 0.238 | |
| Adjusted $\rho^2$ | | 0.230 | | 0.212 | | 0.233 | |

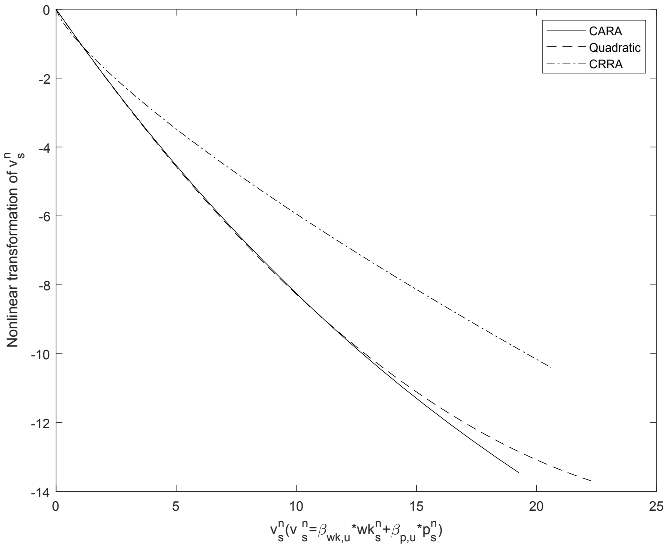


*Figure 3 Nonlinear utility curves, for utility-level form*

*Table 11: Calculated value of time for use on-demand alternative, based on attribute values presented in each replication*

| Replication | Walking time (minutes) | | | Price (£) | | | CARA (£ per hour) | CRRA (£ per hour) | Quadratic utility (£ per hour) | Linear (£ per hour) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lower bound | Most likely value | Upper bound | Lower bound | Most likely value | Upper bound | | | | |
| 1 | 1 | 5 | 10 | 1 | 8 | 10 | 19.08 | 18.50 | 12.18 | |
| 2 | 1 | 8 | 12 | 1 | 3 | 15 | 37.93 | 27.77 | 10.19 | |
| 3 | 1 | 5 | 10 | 1 | 5 | 12 | 19.27 | 17.37 | 13.03 | |
| 4 | 1 | 3 | 15 | 1 | 8 | 10 | 23.13 | 22.28 | 14.93 | |
| 5 | 1 | 3 | 12 | 1 | 3 | 12 | 16.45 | 14.48 | 9.73 | |
| 6 | 1 | 8 | 15 | 1 | 5 | 15 | 51.96 | 37.12 | 3.31 | |
| Mean | | | | | | | 27.97 | 22.92 | 10.56 | 26.20 (±3.37) |
| Utility-level results | | | | | | | 23.02 (±12.72) | 26.41 (±2.68) | 20.84 (±4.22) | |

Note: Calculating standard error values for value of time in the presence of quotients where parameters assumed to be independently normally distributed are divided by one another yields implausibly large estimates; we therefore do not report them here. This issue is addressed in depth in (Hess et al. 2005).

# 6. Summary and Conclusion

Virtual queueing (VQ) and Guaranteed Advance Reservations (GAR) are two mechanisms with potential to address imbalances between supply and demand of free-floating carsharing (FFCS) services. In this paper, we investigate user response to them (as well as the dominant FFCS service model) using a stated-choice approach. The general user behaviour under these three service schemes, and the influence of socio-demographic features and the Big Five personality traits on user behaviour are modelled using discrete choice models.

Respondents exhibit negative willingness-to-pay for VQ, and positive WTP (£0.54 per journey) for GAR, however we studied the context of a social activity purpose ("visiting a friend"), and further research will be needed to establish how these empirical results vary across different activity purposes with different scheduling requirements. We also find that socio-demographics and Big Five personality characteristics both correlate in intuitive ways with FFCS usage and with opting to use these two prospective service attributes relating to fleet availability.

We employ three nonlinear utility models to identify users' risk-taking attitudes towards the 'guaranteed' attributes of GAR versus the uncertain attributes of spontaneous usage. The attribute-level functions, which identify users' distinct risk-taking attitudes towards each of walking time and cost separately suggest risk-seeking with respect to price and insignificant risk-aversion with respect to walking time. The utility-level results, in which a single parameter is estimated for respondents' overall risk-taking behaviour, suggest risk-seeking. This result that respondents are risk-seeking to the combined utility components of time and cost suggest that the positive WTP for GAR may not be attributable to the guaranteed price and vehicle location but instead other attributes such as the guarantee of vehicle access when desired. Further investigation would be needed to discriminate between these hypotheses, as well as to establish whether our finding of risk-seeking with respect to travel cost alongside risk-aversion with respect to travel time is robust across other contexts.

Shared-mobility offers great promise to address inefficiencies related to the private-vehicle ownership model in dense urban areas. The smaller fleet sizes imply that there will be an ongoing challenge to provide users with service reliability that approaches traditional forms of urban transport (e.g. private car ownership and fixed-timetable public transport). "Surge pricing" (Jorge et al. 2015; Xu et al. 2018; Zha et al. 2018) and secondary marketplaces (Le Vine 2014) are two such mechanisms, as are the two mechanisms (VQ and premium-priced GAR) investigated in this research. Future research is needed to investigate the optimality of specific market-making mechanisms in different contexts (including how 'optimal' may differ from the operator's versus the public-policymaker's perspective), as well as possible "mixed" operator strategies of simultaneously providing customers choices of multiple such mechanisms. Research is also needed to investigate how the properties of such mechanisms differ under users engaging in myopic behaviour (as analysed in this research) versus behaving strategically. These challenges imply a need for further development of data-collection approaches such as the stated-choice experiment presented in this paper, as well as validation with empirical observations as and when they become available.

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# Supplementary Material

*Table SM1: Summary of stated-choice experiments in carsharing*

| | Sample size and survey time | Objectives | Attributes | Alternatives | Socio-demographic and attitudinal variables | Fitted model* |
|---|---|---|---|---|---|---|
| (Kim, Rasouli, and Timmermans 2017b) | n=955 (April 2015, the Netherlands) | Round-trip carsharing adoption under uncertain shared vehicle availability | Cost;<br>Time spent on travel;<br>Availability of car-use (uncertain) | Carsharing;<br>Car;<br>Buy an $2^{nd}$ car;<br>PT; | Age;<br>Gender;<br>Household size;<br>Having children and children's age;<br>Education;<br>Income;<br>Satisfaction with current mobility option; | HCM |
| (Kim, Rasouli, and Timmermans 2017a) | n=955 (April 2015, the Netherlands) | Round-trip Carsharing adoption influenced by social distance | Cost;<br>Time spent on travel;<br>Availability of car-use (uncertain);<br>Social influence | Carsharing;<br>Car;<br>Buy an $2^{nd}$ car;<br>PT; | Age;<br>Gender;<br>Household size;<br>Having children and children's age;<br>Education;<br>Income;<br>Satisfaction with current mobility option;<br>Social distance | HCM |
| (Kim, Rasouli, and Timmermans 2017c) | n=791 (April 2015, the Netherlands) | Mode choice under travel time uncertainty of round-trip carsharing | Cost;<br>Time spent on travel (uncertain);<br>Time pressure;<br>Activity duration; | Carsharing;<br>Car;<br>PT | Intrinsic preference for driving;<br>Environmental concern;<br>Symbolic value of car;<br>Privacy seeking | HCM |
| (Ströhle, Flath, and Gärttner 2018) | n=1529 (do not state the survey time and area) | Trade-off of cost and flexibility for round-trip carsharing users | Cost;<br>Walking distance;<br>Scheduled pick-up time; | Carsharing (three alternatives);<br>Opt-out | | ML |
| (Zheng et al. 2009) | n=4141 (in University of Wisconsin-Madison, do not state the time of survey) | Round-trip carsharing adoption | Cost;<br>Walking distance | Two carsharing pricing plans;<br>Opt-out | Gender;<br>Job (faculty, student, etc);<br>Having roommates;<br>Attitudes to car ownership;<br>Environmental concern;<br>Familiarity with carsharing;<br>Truck ownership;<br>Trip purposes with non-private vehicles; | Logistic regression |

| | Sample size and survey time | Objectives | Attributes | Alternatives | Socio-demographic and attitudinal variables | Fitted model |
|---|---|---|---|---|---|---|
| (Jung and Koo 2018) | n=807 (April 2017, South Korea) | Mode choice of round-trip and one-way carsharing | Cost;<br>Vehicle delivery service;<br>One-way allowed;<br>Vehicle type;<br>Fuel type;<br>Fuel charging station supply rate | Carsharing (two alternatives);<br>Opt-out | Age;<br>Education;<br>Income;<br>Environmental concern; | ML |
| (Yoon, Cherry, and Jones 2017) | n=1010 (Summer 2013, Beijing) | Mode choice of round-trip and one-way carsharing | Cost;<br>Time spent on travel;<br>Vehicle type;<br>Decals<br>Weather and air quality | Carsharing;<br>Original mode (bus, cycle, etc.) | Age;<br>Gender;<br>Income;<br>Education;<br>Residential type;<br>Car ownership;<br>Driving license ownership | BNL |
| (Krueger, Rashidi, and Rose 2016) | n=435 (April 2015, Australia) | Mode choice of shared autonomous vehicles | Cost;<br>Time spent on travel | Shared AV (two alternatives);<br>Current mode | Age;<br>Gender;<br>Income;<br>Having children;<br>Car ownership;<br>Carsharing membership;<br>Modality style;<br>Trip purpose and means of transport for the reference trip | ML |
| (de Luca and Di Pace 2015) | n=500 (Spring 2012, South Italy) | Mode choice of one-way carsharing | Cost;<br>Time spent on travel | Carsharing;<br>Car;<br>Carpool;<br>PT | Age;<br>Gender;<br>Trip frequency;<br>Car trip frequency;<br>Home-based trip;<br>Trip origin;<br>Car ownership | MNL;<br>ML |
| (Le Vine et al. 2014) | n=72 (February-March 2011, London) | Round-trip and free-floating carsharing adoption and mode choice | Cost;<br>Time spent on travel | Carsharing;<br>Car;<br>PT;<br>Taxi;<br>Walk;<br>Cycle | | MNL |
| (de Luca and Di Pace 2014) | n=962 (in South Italy, do not state the survey time) | Mode choice of one-way station-based carsharing | Cost;<br>Time spent on travel;<br>Carpooling | Carsharing;<br>Car (as driver or passenger);<br>Bus | Gender;<br>Trip frequency;<br>Car ownership; | BNL<br>ML |
| (Catalano, Casto, and Migliore 2008) | n=495 (in Palermo, Italy; do not state the survey time) | Mode choice of one-way station-based carsharing | Cost;<br>Time spent on travel | Carsharing;<br>Car;<br>PT;<br>Carpooling | | MNL;<br>NL |
| (Hironori, Akihiro, and Takahiro 2013) | n=208+275+158+365 (February to April 2010, Japan) | Carsharing adoption and mode choice of carsharing | Cost;<br>Time spent on travel | Carsharing;<br>Car;<br>Bus;<br>Rail | Gender;<br>Income | BNL |

| | Sample size and survey time | Objectives | Attributes | Alternatives | Socio-demographic and attitudinal variables | Fitted model |
|---|---|---|---|---|---|---|
| (Cartenì, Cascetta, and de Luca 2016) | More than 600 (in South Italy; do not state the survey time) | Carsharing adoption (the carsharing stations are Outside of the city. Customers park private cars there and change to carsharing vehicles) | Cost;<br>Time spent on travel;<br>Having EV | Carsharing;<br>Car | Age;<br>Gender<br>Car ownership;<br>Trip frequency;<br>Employment status;<br>Trip purpose;<br>EV preference | BNL |
| (Zoepf and Keith 2016) | 3958 (October 2013, U.S.) | Trade off of cost and flexibility for round-trip carsharing users;<br>Fuel type | Cost;<br>Walking distance;<br>Scheduled pick-up time;<br>Fuel type | Carsharing (four alternatives);<br>Opt-out | Having children;<br>Typical trip length;<br>Current mobility option;<br>City where carsharing is used;<br>Typical leading time for reserving carsharing vehicles | MNL;<br>ML |

* Abbreviations as follows:

BNL: binomial logit model
HCM: hybrid choice model
ML: mixed logit model
MNL: multinomial logit model
NL: nested logit model

*Table SM2: Questions used to determine the 'Big Five' personality traits*

How well do the following statements describe your personality?

| I see myself as someone who… | Disagree strongly | Disagree a little | Neither agree nor disagree | Agree a little | Agree strongly |
|---|---|---|---|---|---|
| … is reserved (Q1) | (1) | (2) | (3) | (4) | (5) |
| … is generally trusting (Q2) | (1) | (2) | (3) | (4) | (5) |
| … tends to be lazy (Q3) | (1) | (2) | (3) | (4) | (5) |
| … is relaxed, handles stress well (Q4) | (1) | (2) | (3) | (4) | (5) |
| … has few artistic interests (Q5) | (1) | (2) | (3) | (4) | (5) |
| … is outgoing, sociable (Q6) | (1) | (2) | (3) | (4) | (5) |
| … tends to find fault with others (Q7) | (1) | (2) | (3) | (4) | (5) |
| … does a thorough job (Q8) | (1) | (2) | (3) | (4) | (5) |
| … gets nervous easily (Q9) | (1) | (2) | (3) | (4) | (5) |
| … has an active imagination (Q10) | (1) | (2) | (3) | (4) | (5) |

Scoring the BFI-10 scales:

Extraversion: 1R, 6 (i.e. simple average of the 'reverse' score of Q1 [with '5' re-coded to '1', '4' to '2', etc.] and Q6);

Agreeableness: 2, 7R;

Conscientiousness: 3R, 8;

Neuroticism: 4R, 9;

Openness: 5R, 10

*Above reproduced from: (Rammstedt and John 2007)*

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