THE INCORPORATION OF BUDGET CONSTRAINTS WITHIN STATED CHOICE EXPERIMENTS TO ACCOUNT FOR THE ROLE OF OUTSIDE GOODS AND PREFERENCE SEPARABILITY

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ABSTRACT

Stated choice (SC) experiments are a popular means of collecting preference data for discrete alternatives. Many SC experiments include a no choice alternative, either as an opt out or as a status quo alternative. Even in the presence of a no choice alternative, it is not clear that respondents understand fully the trade-offs being made between the choice alternatives, and other outside goods. As such, it is possible that many SC experiments are in violation of one of the central tenets underlying the micro-economic theory of demand. In this paper, we report two studies, in which respondents are required to indicate how they would readjust their household budget in light of choices made in a SC experiment. In both case studies, we find significant differences in the results obtained between traditional SC tasks and tasks involving the reallocation of household budgets. We argue that tasks involving the reorganisation of the household budget, are at least in part, more incentive compatible given that respondents are faced with the financial consequence of their choices, as well as bound by their true budget constraint. The results of the paper reaffirms classical micro-economic demand theory with respect to SC experiments.

JEL classifications: C35, C83, C99, D01, D12, D14.

Keywords: *Stated choice experiment, multiple discrete continuous extreme value model, household budget, preference separability, incentive compatibility*

1.0 INTRODUCTION

Originating in the field of psychology in the 1930s (Thurstone 1931), stated choice (SC) methods have become widely used as a means of collecting data to model consumer preferences. Early proponents of SC methods made use of crude experimental designs to construct surveys in which respondents were asked to make pairwise comparisons between competing hypothetical alternatives. These early researchers were able to derive indifference curves representing the preferences of the sampled respondents and later test the axioms underlying indifference curves and hence consumer demand theory itself (MacCrimmon and Toda 1969, May 1954, Mosteller and Nogee 1951, Rousseas and Hart 1951, Thurstone 1931). Numerous advances have occurred since. Paralleling improvements in computing, advances in econometric modelling have also occurred, allowing researchers to deal with multinomial choices (McFadden 1974), model complex forms of heterogeneity (e.g., the mixed multinomial logit model - Train et al. 1987 - or the latent class model - e.g., Kamakura and Rusell 1989) as well as other effects associated with SC data, such as the possibility that multiple choice observations (repeated measures) can be obtained for each respondent (see e.g., Revelt and Train 1998). Additionally, experimental design theory specifically for SC type data also has advanced considerably over the past three decades (see Rose and Bliemer 2014a for a review of the literature on SC experimental design theory).

Nevertheless, from its very inception, many economists have criticized the use of SC experiments, claiming that the hypothetical nature of such experiments will result in respondents systematising their answers in such a way as to produce plausible but spurious results (Wallis and Friedman 1942). The same arguments against the use of SC surveys remain today (e.g., Camerer and Hogarth 1999; Diamond and Hausman 1994; Fifer et al. 2014, List 2001, Krucien et al. 2015). Indeed, encapsulated by the concept of incentive compatibility, there exists growing evidence supporting the early criticisms of Wallis and Friedman (1942) that respondents acting in a utility maximising manner may behave strategically rather than reveal their true preferences when answering SC surveys (e.g., Carson and Groves 2007).

Given the continued need to provide forecasts and inputs into benefit cost ratio (BCR) calculations for new or emerging technology and large scale infrastructure projects, as well as to derive estimates as to the value of non-market goods for purposes of policy analysis, a number of researchers, rather than abandon SC experiments, have explored alternative strategies to either stimulate respondents to act identically to how they would behave if faced with similar choices in real markets, or minimise any biases that might arise if they were to not make choices that reflect their true preferences. Recent attempts to make SC choice tasks more realistic and less prone to hypothetical bias have taken many forms. Making SC choice tasks more incentive-compatible by increasing the consequentiality of the choices made by ensuring that respondents face some real outcome or consequence from the choices they make, referred to as incentive alignment (e.g., Ding 2007, Harrison 2007, Vossler and Evans 2009, Herriges et al. 2010), or via the individual customisation of SC choice tasks to decision maker specific experiences (e.g., Rose et al. 2008; Train and Wilson 2008), represent just two approaches researchers employ.

The incentive compatibility requirement that respondents experience one of their choices may not always be feasible, particularly when the experiment involves some new hypothetical alternative or technology (e.g., a new metro mode that is yet to be built), some non-market good that may not be readily accessible to them (e.g., a study designed to value the protection of a river system in Africa), a scenario in which the alternatives are particularly costly (e.g., new car choice), or requires extensive clinical trials before release to the market (e.g., a new cancer fighting medication). As a consequence, most studies tend to ignore the issue completely or rely on the soft approach of reminding respondents about the impact their choices will have on their current expenditure patterns, as with the “cheap talk” technique (e.g., Arrow et al. 1993). Even with such reminders, however, it is possible for respondents undertaking SC tasks to ignore or underestimate their true budget constraints, which will significantly impact on the study outcomes. Wardman (2001) and Brownstone and Small (2005) both argue that respondents tend to ignore budget constraints and select higher-cost alternatives more frequently in hypothetical surveys as opposed to in real life.

A further potential issue with SC surveys lies in the ability of respondents to complete lengthy questionnaires. Whilst there exists no restriction as to how much information respondents can provide analysts in theory, empirically respondents are only able to provide a finite amount of information before becoming bored or cognitively impaired. As such, SC experiments are typically constrained to examine only a single choice context (e.g., work trip mode choice, choice of headache medication, preference for alternative environmental policies related to a specific river system). Such a restriction limits the consumption set available to individual decision makers to a set of finite alternatives defined by the context being examined. For example, in applied transportation studies involving mode choice, the choice set faced by individual decision makers will be defined by the alternative modes of transport available to them given a specific trip context. Thus, SC experiments are always devised under the assumption of preference separability, and hence assume that substitution and trade-off effects occur only within a subset of consumption over an exogenously determined portion of the budget (e.g., Deaton and Muellbauer 1980). Preference separability only holds, however, if the prices (and non-price attributes) of all goods outside of the consumption set under direct consideration are the same for all decision makers (e.g., Deaton 1974). This assumption is unlikely to hold in practice, in which case SC experiments are no longer consistent with basic micro-economic theory.

Demand analysis, as derived from micro-economic theory, is a powerful tool for the measurement of the behavioural and distributional effects of counterfactual price, income and quality changes. Typical demand analysis research involves the estimation of the unknown parameters of a parametric demand system, which are then applied to calculate a post-reform change in demand as well as calculate any corresponding changes to welfare that might occur (e.g., Banks et al. 1997). Early economic theorists working on demand analysis developed the conceptual framework of utility trees to describe the budget allocation of individual agents (e.g., Furubotn 1963, Gorman 1959, Stotz 1957, 1959), noting that under consumer theory, commodities that are close substitutes are more likely to satisfy the same need, and hence belong to the same branch or hierarchy within the utility tree than commodities that are not substitutes (Drakopoulos 1994). This led to the now frequently imposed assumption in both theoretical and applied demand studies known as weak separability of utility, where a group of goods is deemed to be weakly separable if the marginal rate of substitution (MRS) between any two goods in the group is independent from the quantities consumed of any outside good, or strongly separable if the value of a commodity is independent of the MRS between any two goods located in a separate utility branch (e.g., Leontief 1947; Sono 1961, Stotz 1959).

The assumption of separable preferences is ubiquitous in studies of aggregate level demand, with numerous studies providing examples of micro-economically rigorous simultaneous-equation models of consumer demand for goods and services which are consistent with the idea of weak utility separability (e.g., Deaton 1987, Deaton and Muellbauer 1980, Lau 1986, Pollack and Wales 1978 and Stone 1954). To date, these empirical studies have mostly made use of revealed preference data and tended to rely on two main approaches to test for preference separability; (i) the use of econometric methods to verify certain parameter restrictions on a given demand model, and (ii) tests related to the generalised axiom of revealed preference (GARP) (see Afriat 1967, Varian 1982, Diewert and Parkan 1985) that assess whether the revealed preference conditions that characterise the collection of data sets that are rationalisable by a (weakly or strong) separable utility function hold.

Specifically, Varian (1983) developed a test for the joint hypothesis of separability and concavity of utility that involves solving a system of polynomial inequalities. This test was later operationalised by Cherchye et al. (2015). Subsequently, Browning and Meghir (1991) developed a parametric econometric test for preference separability based on revealed preference data. More recently, Quah (2012) developed an alternative process to test for separability alone, without the assumption of concavity of utility, however the test developed makes severe restrictions on the number of goods that can be considered. Independent of the above research, Blundell et al. (2003, 2007, 2008) developed a nonparametric test for separability restrictions.

Whilst there exist some studies involving disaggregate level demand data that are concerned with the topic of preference separability, such concerns appear yet to be discussed within the framework of SC data. Nevertheless, many SC experiments include an opt-out alternative, which implicitly acknowledges the presence of outside goods in the data generation process. As noted by Rose and Hess (2009) however, there exist multiple representations of how opt out alternatives have been included within SC surveys. Traditionally, the opt out alternative was presented to respondents either as a ‘none’ alternative devoid of any attribute levels, or alternatively as an option labelled as ‘your current alternative’ with attribute levels given simply as “at the current level” (see e.g., Dhar 1997). More recently, for studies dealing with environmental goods, it is not uncommon to provide respondents with a status quo alternative described by levels which are invariant across respondents.

Somewhat different is the transportation literature where it is now common to use as an opt out alternative, a reference alternative constructed using levels related to some recent experience as reported by the respondent undertaking the questionnaire. Unfortunately, different types of opt out alternatives may induce different types of responses arising from interpretational discrepancies, and even when interpretation is consistent between respondents, differences may arise due to perceptual or preference differences.

In the current paper, we seek to examine the role outside goods have on SC experiments. In doing so, we propose a method that also potentially has implications for the incentive compatibility of such experiments. Reported herein are two empirical studies in which respondents completing SC experiments were also tasked with having to reallocate their existing household budget in order to accommodate the associated costs of their choices. Whilst the context of both studies is vehicle choice, in the first study, we provide a within subject comparison between a traditionally framed choice task and one requiring the additional household budget reallocation assignment, whilst the second study involves a between subject comparison involving similar question treatments. For the first study, we find significant changes in the choices made by respondents when they are required to also complete the household budget reallocation task. Surprisingly, whilst the second task is likely to induce substantial more cognitive burden to complete, we found over 20 percent of the sample opting into the market after originally selecting the no choice alternative in the more traditional task. In the second study, we also find substantial differences between the results obtained from the two tasks. In both cases, we provide a more realistic choice scenario, whereby respondents are also able to adjust the impact of their choices in the SC task by making additional choices, such as using savings or money earned from selling existing vehicles to offset the cost of purchasing a vehicle in the SC questions asked. It is our argument that allowing for a more realistic set of interrelated choice outcomes, is likely to improve the incentive compatibility of SC tasks. Further, we argue that by forcing respondents to reallocate their existing household budget based on related choices observed in a SC experiment, respondents are directly confronted with the budgetary impact of their choices, further adding to the incentive compatibility of the survey task performed.

The remainder of the paper is structured as follows. In Section 2, we discuss the within subject case study, where respondents are first exposed to a traditional choice task, after which they are confronted with the same task, but the additional requirement to indicate how they would reallocate their household budget based on their observed choice. Next, Section 3 details a second study, involving a between subjects comparison similar to that undertaken by respondents involved in the first study. Here we demonstrate how such data can be modelled in a single framework, involving the estimation of discrete choice models alongside a multiple discrete continuous model. Finally, Section 4 provides a general discussion and conclusion to the paper.

2.0 STUDY I

2.1 Survey

Respondents were asked to complete an internet questionnaire related to vehicle choice with several sections (shown in Figure 1). After providing consent to participate in the survey, respondents were asked to indicate how much their household spends in a typical month on a number of common expenditure categories (see Figure 2). Next, respondents were asked a series of questions related to their current vehicle fleet, after which they were asked were to complete a stated choice (SC) experiment consisting of four forced choice SC questions. So as to order to capture market size variability impacts, each of the four SC tasks consisting of a variable number of alternatives (between two and eight) represented as different vehicle body types and colour schemes, which were further described by a set of 12 attributes. These included the year of manufacture of the vehicle, the number of kilometres the vehicle had on its odometer (constrained to zero if the vehicle was manufactured in 2015), how many seats the vehicle had, the type of fuel the vehicle used (consisting of engines which are pure electric, hybrid, diesel or petrol), the number of cylinders (constrained to zero for pure electric vehicles), and the range of the vehicle if the vehicle had a pure electric engine.

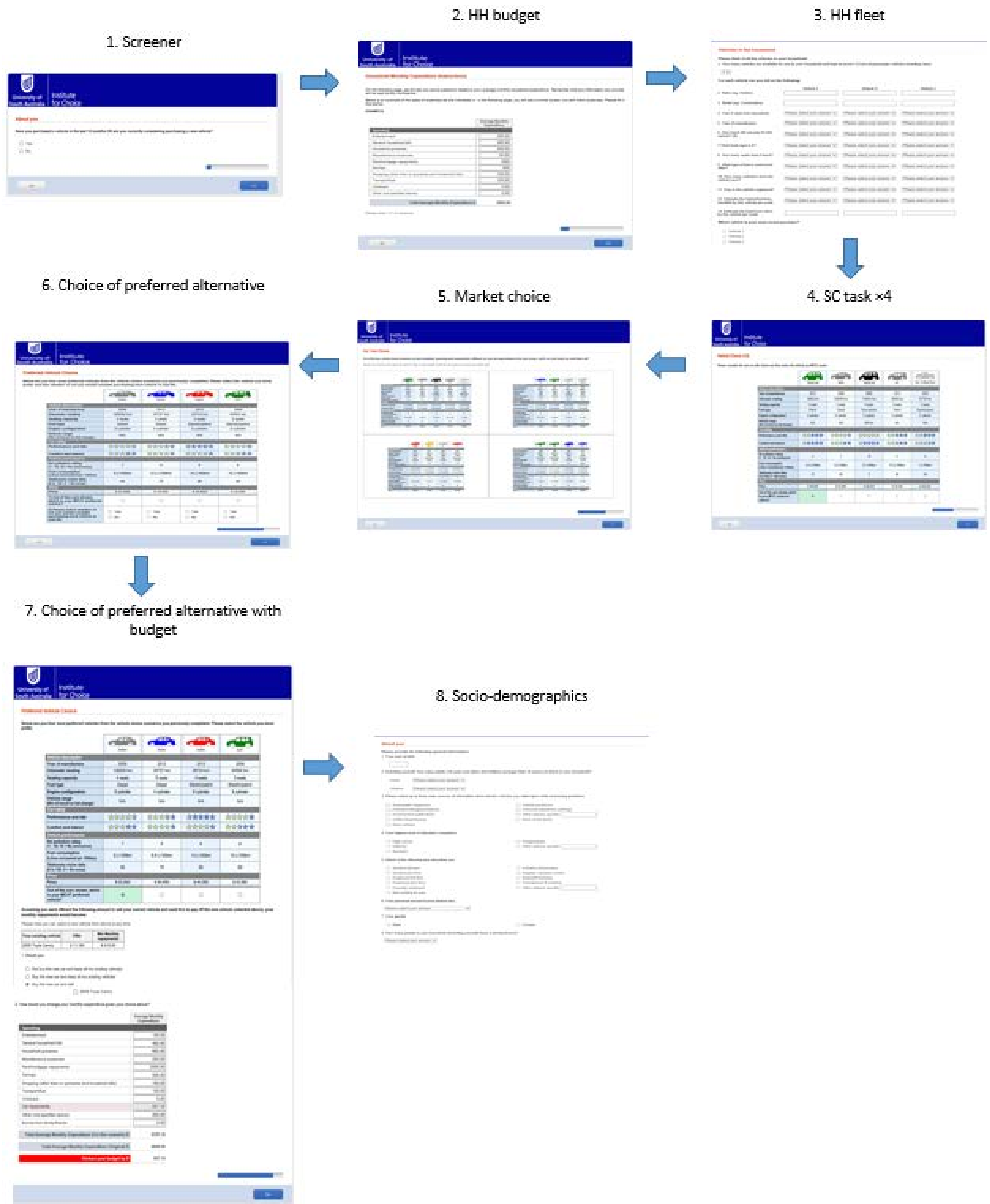


Figure 1: Study 1 survey structure

Other attributes included a rating system describing the vehicle ride performance and level of comfort of the interior. The rating system adopted to describe these attributes was based on real car sale websites (in particular http://www.caradvice.com.au/). The remaining attributes describe the air pollution rating of the vehicle based on a 0 to 10 point scale, the vehicle fuel consumption level, and a variable that describes the amount of noise when at rest of the vehicle (also on a 0 to 10 point scale). The noise and air pollution rating attributes were based on the green vehicle guide website established by the Australian Federal government (http://www.greenvehicleguide.gov.au/GVGPublicUI/Search.aspx).The final attribute was the price of vehicle. A Bayesian efficient experimental design was implemented based on priors obtained from a previous study that made use of similar stated choice survey questions (see Rose and Bliemer 2014b). The design allowed for variable choice set sizes, as described in Rose et al. (2013).

Household Monthly Expenditure (Instructions)

On the following page, we will ask you some questions related to your average monthly household expenditure. Remember that any information you provide will be kept strictly confidential.

Below is an example of the types of expenses we are interested in. In the following page, you will see a similar screen, but with blank expenses. Please fill in the blanks.

EXAMPLE

	Average Monthly Expenditure
Spending	
Entertainment	250.00
General household bills	350.00
Household groceries	300.00
Miscellaneous expenses	80.00
Rent/mortgage repayments	1000
Savings	500
Shopping (other than on groceries and household bills)	100.00
Transport/fuel	100.00
Childcare	0.00
Other (not specified above)	0.00
Total Average Monthly Expenditure $	2680.00

Figure 2: Household monthly expenditure

After completing the four forced choice tasks, respondents were next presented with a screen showing simultaneously the four SC screens, and asked which of the four choice tasks they would most prefer to visit when looking to purchase a vehicle, assuming each individual market represented a different car yard or market. After making a choice of choice task, respondents were presented with a fifth vehicle choice task, which consisted four alternatives, these being the alternatives selected in the first four SC questions. An example choice task, based on this question is shown in Figure 3.

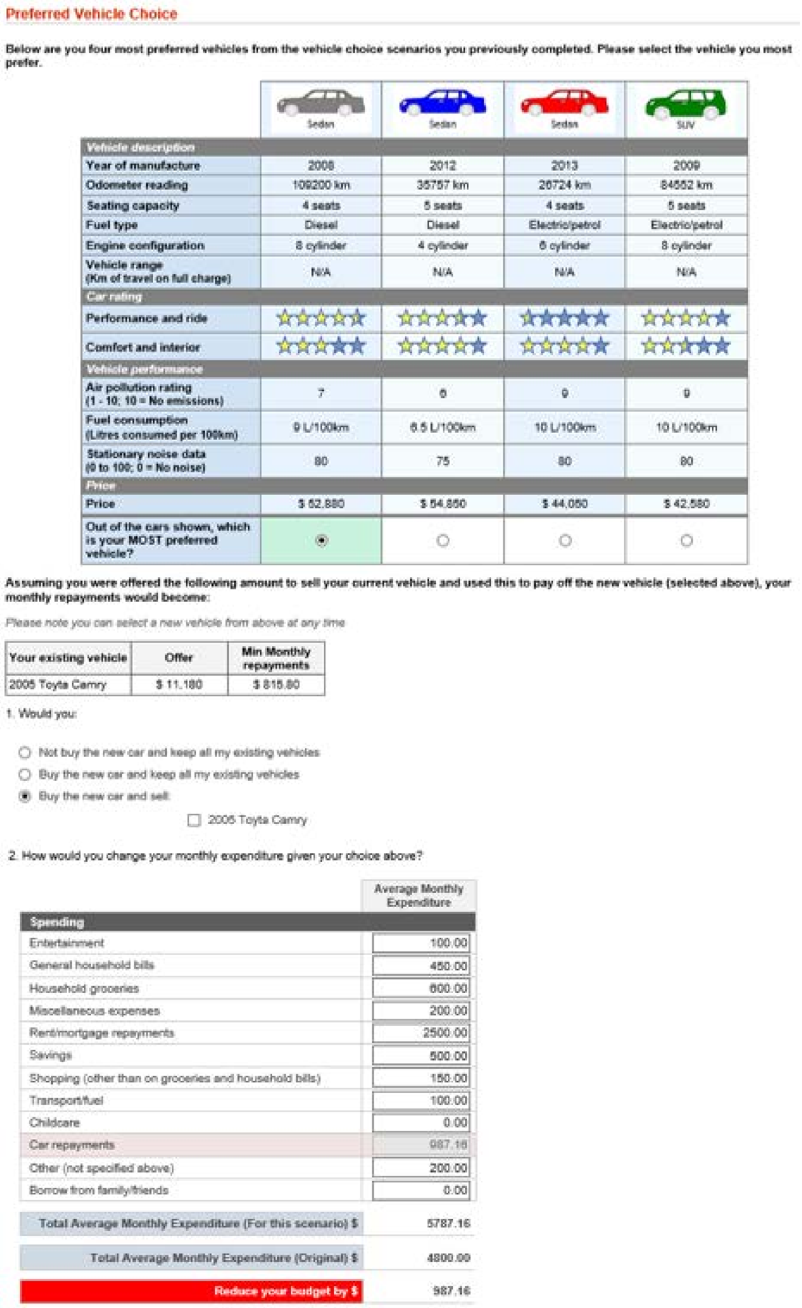
Preferred Vehicle Choice

Below are you four most preferred vehicles from the vehicle choice scenarios you previously completed. Please select the vehicle you most prefer and also whether or not you would consider purchasing each vehicle in real life.

	Sedan	Sedan	Sedan	SUV
Vehicle description				
Year of manufacture	2008	2012	2013	2009
Odometer reading	109200 km	35757 km	26724 km	84552 km
Seating capacity	4 seats	5 seats	4 seats	5 seats
Fuel type	Diesel	Diesel	Electric/petrol	Electric/petrol
Engine configuration	8 cylinder	4 cylinder	6 cylinder	8 cylinder
Vehicle range (Km of travel on full charge)	N/A	N/A	N/A	N/A
Car rating				
Performance and ride	★★★★½	★★★½☆	½☆☆☆☆	★★★★☆
Comfort and interior	★★★☆☆	★★★★☆	★★★★☆	★★½☆☆
Vehicle performance				
Air pollution rating (1 - 10; 10 = No emissions)	7	6	9	9
Fuel consumption (Litres consumed per 100km)	9 L/100km	6.5 L/100km	10 L/100km	10 L/100km
Stationary noise data (0 to 100; 0 = No noise)	80	75	80	80
Price				
Price	$ 52,880	$ 54,850	$ 44,050	$ 42,580
1) Out of the cars shown, which is your MOST preferred vehicle?	○	○	○	○
2) Please select whether or not you would consider purchasing each vehicle in real life:	○ Yes ○ No	○ Yes ○ No	○ Yes ○ No	○ Yes ○ No

Figure 3: Study I example choice screen

Next, respondents where shown a repeat of the previous choice task (consisting of the four preferred vehicles based on the initial four choice tasks completed), however this time, in addition to being shown the overall vehicle price, respondents were also shown the monthly repayments for their selected vehicle, as well as being given an offer price for selling any of their existing vehicle fleet, and an adjustment to the minimum monthly repayments should they sell any of their existing vehicles. At the bottom of the screen, their monthly household budget given earlier in the survey was shown back to them. With this additional information, respondents where then asked an additional choice question, consisting of whether they would not buy any of the vehicles shown, purchase their preferred vehicle and if the vehicle was to be purchased, whether they would keep all their existing vehicles or sell one or more of them. Respondents were able to change their preferred vehicle from that selected in the previous task, and in doing so the repayments required that were shown were also adjusted, but not the offer prices of vehicles in their existing fleet. For respondents who elected to purchase any of the vehicles shown, they were next tasked with having to adjust their monthly household budget to account for how they would meet the vehicle repayments. An example of this task is shown in Figure 4.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Fuel type	Diesel	Diesel	Electric/petrol	Electric/petrol
Engine configuration	8 cylinder	4 cylinder	6 cylinder	8 cylinder
Vehicle range (Km of travel on full charge)	N/A	N/A	N/A	N/A
Car rating				
Performance and ride				
Comfort and interior				
Vehicle performance				
Air pollution rating (1 - 10; 10 = No emissions)	7	6	9	9
Fuel consumption (Litres consumed per 100km)	9 L/100km	8.5 L/100km	10 L/100km	10 L/100km
Stationary noise data (0 to 100; 0 = No noise)	80	75	80	80
Price				
Price	$ 52,880	$ 54,850	$ 44,050	$ 42,580
Out of the cars shown, which is your MOST preferred vehicle?	◉	○	○	○

Assuming you were offered the following amount to sell your current vehicle and used this to pay off the new vehicle (selected above), your monthly repayments would become:

Please note you can select a new vehicle from above at any time

Your existing vehicle	Offer	Min Monthly repayments
2005 Toyta Camry	$ 11,180	$ 815.80

1. Would you:

○ Not buy the new car and keep all my existing vehicles
○ Buy the new car and keep all my existing vehicles
◉ Buy the new car and sell:
☐ 2005 Toyta Camry

2. How would you change your monthly expenditure given your choice above?

Spending	Average Monthly Expenditure
Entertainment	100.00
General household bills	450.00
Household groceries	600.00
Miscellaneous expenses	200.00
Rent/mortgage repayments	2500.00
Savings	500.00
Shopping (other than on groceries and household bills)	150.00
Transport/fuel	100.00
Childcare	0.00
Car repayments	987.16
Other (not specified above)	200.00
Borrow from family/friends	0.00
Total Average Monthly Expenditure (For this scenario) $	5787.16
Total Average Monthly Expenditure (Original) $	4800.00
Reduce your budget by $	987.16

Figure 4: Study I example choice screen with budget adjustment question

The final section of the survey involved respondents answering questions about themselves as well as providing general information about their household. Information collected included data on the respondent's age and gender, highest education attained, employment status, annual income before tax, as well as the number of adults and children living in their household at the time of the survey.

2.1.1 Sample

A total of 1,000 respondents completed an internet based survey, sampled using the internet panel PureProfile (www.pureprofile.com). The survey was conducted the week commencing the 13th April 2015. Eligible respondents, drawn from the Australian population, had to be over 18 years of age and either have purchased a vehicle in the past 12 months or be currently in the market to buy a vehicle in the next 12 months. Respondents were asked at the commencement of the survey to provide information related to their average monthly spending for a range of typical household expenditure items, including savings (see Figure 1). Data from 88 respondents were removed during data cleaning as a result of providing what was considered to be nonsensical answers to the household expenditure question (e.g., spending zero dollars for food, or reporting a total expenditure that was less than their own net income levels), thus resulting in data from 912 respondents being available for use in the final analysis.

Of the final sample, 14.20 percent of respondents had reported purchasing a vehicle in the previous 12 months with the remainder being in the market for a new vehicle. Further, 1.21 percent of respondents reported belonging to a household that does not currently own a vehicle and hence were in the market for an automobile for the first time. The remaining respondents reported belonging to households with an average vehicle ownership of 1.61 vehicles, with 47.81 percent of households having one vehicle, 41.67 percent two vehicles and the remaining 9.32 percent having three or more vehicles. The average price paid for a vehicle at the time of purchase was $23,191.49 with a median year of manufacture being 2007 and year of purchase 2012. The average age of the respondents was 48.83, with 52.08 percent being female. Average personal net income reported for the sample was $36,861.29 per annum, and for the sample, the average household size was 2.75, consisting of 2.05 adults and 0.70 children.

2.1.2 Results

Given the nature of the data, we do not report models but rather explore descriptively how respondents change their choices between the two comparable tasks, with and without the budget reallocation task. The decision not to estimate models was based on two factors. Firstly, the pre and post budget questions were captured for only a single choice task, which provided very poor model results when accounting for the large number of attributes and alternatives over such a small number of observations. Secondly, as will be discussed below, changes in choices between the two tasks where observed to be mainly confined to respondents either changing their initial vehicle choice to the no choice alternative, or selecting a vehicle after initially choosing none of the available vehicle alternatives. Very few changes where observed to have occurred between vehicles shown within the choice tasks. Such choice behaviour, alongside the complexity of the task itself, provides little understanding of the marginal utilities of the individual attributes, but rather provides interesting insights into what role the outside goods, as portrayed via the household budget items, plays on the choice process.

Table 1 presents a cross tabulation of the choice data captured in the first study. Within the table, the row totals reflect the number of times a particular vehicle type was selected in the first task (without budget reallocation), whilst the column totals reflect the number of times a vehicle type was chosen in the second task when respondents were asked to indicate how they would change their monthly household budget given the vehicle repayments required given the vehicle chosen. For example, from the table it can be seen that 40 respondents selected a station wagon as their preferred vehicle in the first task, whilst 54 respondents chose a station wagon as their preferred vehicle in the second task. The leading diagonal of the table reflects the number of times respondents selected the same alternatives in both tasks. For example, 21 respondents selected a station wagon in both tasks (i.e., did not change their initial choice), whilst 52 choose the same SUV in both tasks. Three hundred and fifteen respondents choose none of the vehicles in both tasks. Within the table, elements shown above the leading diagonal in light grey relate the number of respondents who changed their choice upon being asked to indicate how they would have to change their monthly household budget based on their vehicle choice. Thus for example, of the 40 respondents who chose a station wagon as their most preferred vehicle in the first task, two of those choose an alternative vehicle (i.e., one to a coupe and one to a ute/4 wheel drive) whilst 17 switched their choice to the no choice alternative. Four respondents selected a different vehicle of the same body type, as shown in the column titled ‘Same body type’. One hundred and fifty five respondents changed their choice from one vehicle to no vehicle when asked to complete the household budget component in the second task. Elements below the leading diagonal in the table show which vehicle types respondents switched from. For example, 32 respondents who chose the no choice alternative in the first task, chose a station wagon in the second task, whilst one who had selected an SUV switched to a station wagon. In total, 202 respondents who chose no vehicle in the first task, selected a vehicle when asked to complete the household budget component in the second task.

Table 1: Study 1 results

	Convertible	Station wagon	Ute/4WD	Sedan	Coupe	Hatch -back	Family van	SUV	Same body type	None	Total (no budget)
Convertible	**11**	0	0	0	0	1	0	0	0	3	**15 (1.64%)**
Station wagon	0	**21**	1	0	1	0	0	0	0	17	**40 (4.39%)**
Ute/4WD	0	0	**24**	0	0	0	0	0	0	19	**43 (4.71%)**
Sedan	0	0	0	**46**	0	0	0	0	1	22	**69 (7.57%)**
Coupe	2	0	0	0	**16**	0	0	0	1	23	**42 (4.61%)**
Hatch back	0	0	0	0	0	**35**	0	0	0	31	**66 (7.24%)**
Family van	0	0	0	0	0	0	**16**	0	1	6	**23 (2.52%)**
SUV	0	1	0	0	0	0	0	**52**	1	34	**88 (9.65%)**
Same body type	0	0	0	1	1	0	1	1	**0**	0	**4 (0.44%)**
None	15	32	26	35	21	25	19	34	0	**315**	**522 (57.24%)**
Total (budget)	**28 (3.07%)**	**54 (5.92%)**	**51 (5.59%)**	**82 (8.99%)**	**39 (4.28%)**	**61 (6.69%)**	**36 (3.95%)**	**87 (9.54%)**	**4 (0.44%)**	**470 (51.54%)**	**912 (100%)**

In total, 376 or 41.23 percent of respondents altered their initial choice when asked to detail how they would have to change their monthly household budget to pay for their preferred vehicle. Of the 155 who originally selected a vehicle but later elected no vehicle in the second task, the median vehicle price for the vehicles shown in the two tasks was $27,115 (mean $34,529.40), representing an average monthly repayment of $637.82, translating to approximately 25.50 percent of the monthly household budget for these respondents. In comparison, for the 202 respondents who selected none of the vehicles in the initial task but elected to purchase a vehicle in the second task, the median vehicle price was $27,510 (mean $30,160.14), representing an average monthly repayment $560.68, or 19.21 percent of household monthly budget of these respondents.

Of the 536 respondents who retained their initial vehicle choice in the second task, 315 chose none of the vehicles in both tasks. The median vehicle price for these respondents was $29,112.50 (mean $39,757.73), with an average monthly repayment of $742.20 per month, or 27.82 percent of the household monthly budget for these respondents. Of the remaining 221 respondents who selected the same vehicle in both tasks, the median vehicle cost for all vehicles shown in the two tasks was $25,225 (mean $30,196.25) with an average monthly repayment of $576.64, representing 18.55 percent of the monthly budget for these respondents.

Based on the above results, there appears to exist some threshold in terms of the amount of monthly repayments required when purchasing a vehicle as a proportion of the total monthly household budget. In the aggregate, when repayments exceed 20 percent of the household budget, respondents elect not to purchase any of the vehicles, whereas repayments less than 20 percent of the total household budget tend to result in the decision to purchase a vehicle.

3 STUDY II

3.1 Survey

As with those who completed the survey in the first study, respondents recruited to the second study were tasked with completing an online questionnaire that involved several different survey sections. As before, after obtaining consent from the respondent, the survey started by asking respondents to provide information as to their monthly household budget, in addition to any savings they had, which had not been asked in study I. Next, answers to questions relating to the existing vehicle fleet of the household were captured, after which respondents were introduced to a SC experiment. Unlike the first study however, respondents were randomly assigned to one of two treatment groups. Respondents assigned to the first treatment group (referred to as G1 hereafter) completed four SC tasks, involving vehicle choice using the same experimental design setup developed for the first study. As such, respondents were exposed to several alternative vehicles and asked to select their most preferred vehicle from the set shown, with the number of vehicles shown in each task varying from two to eight according to the same availability design employed in Study I. The attributes and attribute levels were also those used for the first study. The main difference between the choice tasks used for Study I and those for those assigned to treatment group G1 in Study II lies with the response mechanism employed. Whilst both experiments asked respondents to first select their most preferred vehicle from those shown, respondents in G1 where subsequently shown the repayments required for the selected vehicle and asked given the repayment value if they would not purchase their preferred vehicle, buy the preferred vehicle and keep all vehicles in their existing fleet, or buy the preferred vehicle and sell one or more of the current household vehicles. A further difference between the two studies meant that those involved in Study II where also able to allocate any savings they currently have towards the purchase of the new vehicle, therefore minimising the monthly repayments required. Figure 5 shows an example choice task for those assigned to G1. In the example, the respondent previously indicated that household had zero savings available to them (an example of the household savings allocation task is given in Figure 6).

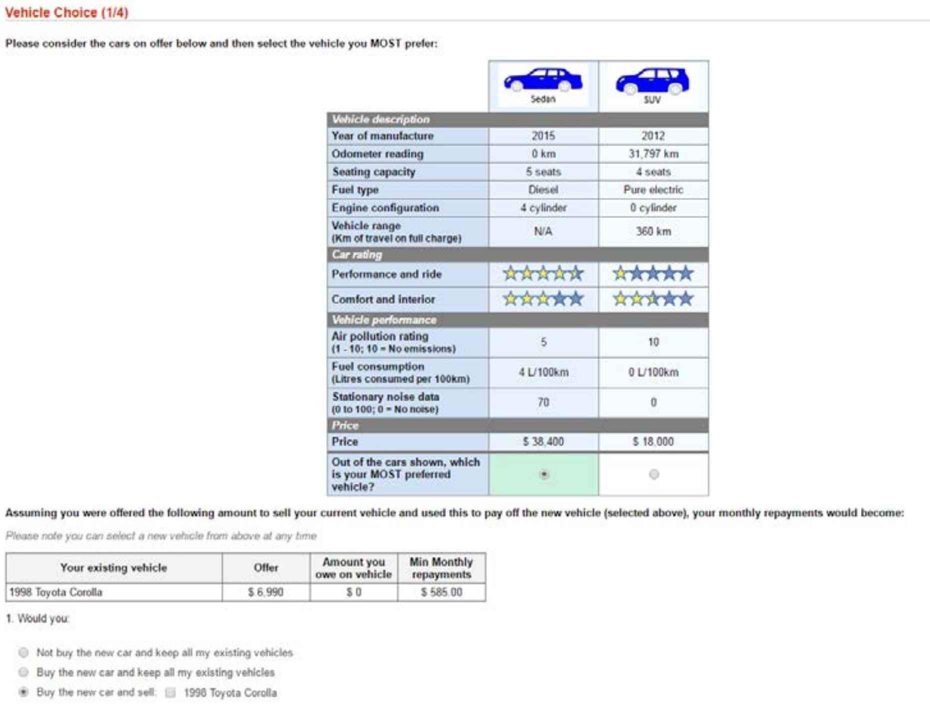


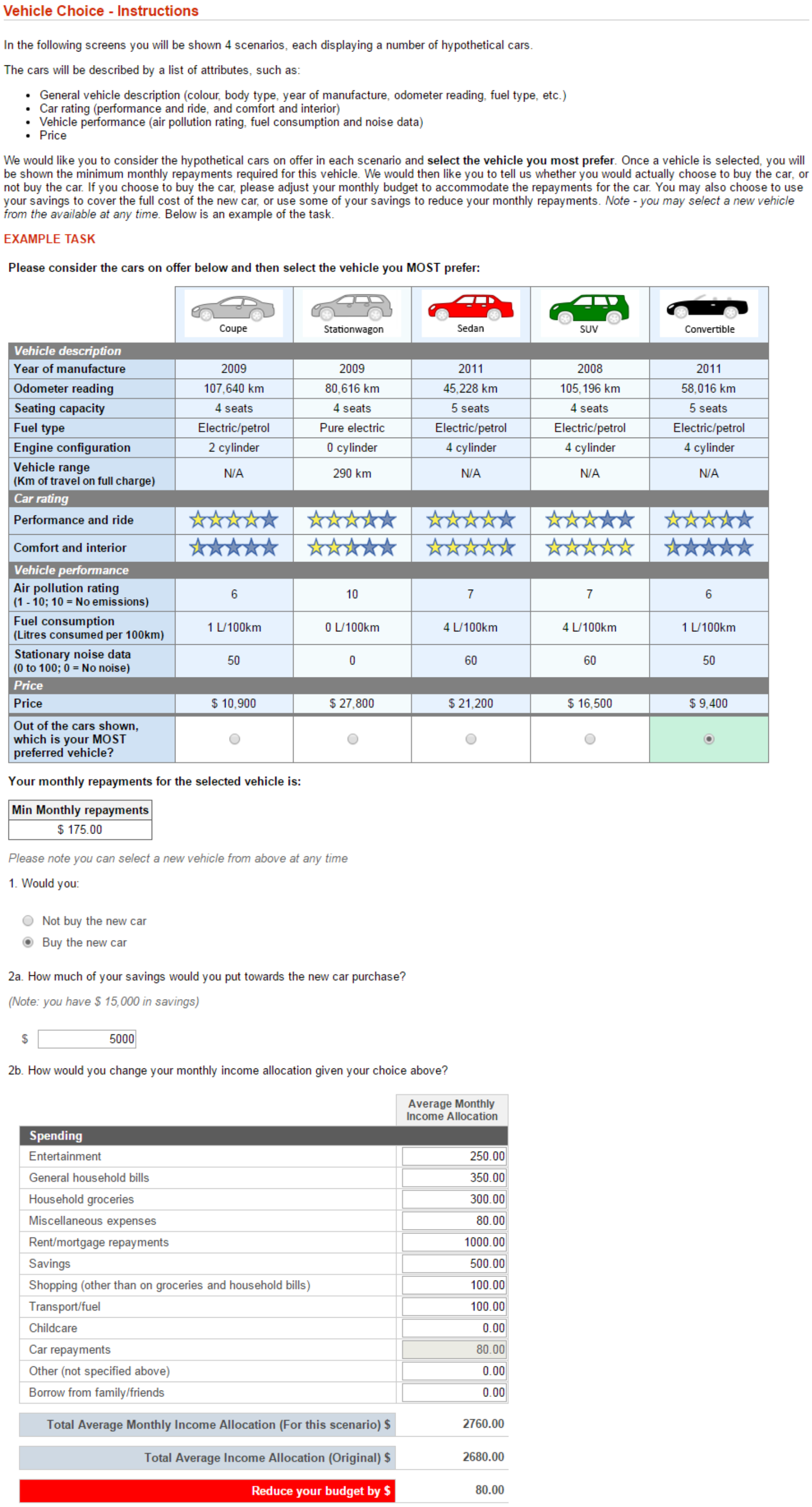
Figure 5: Study II example choice screen shown to treatment group 1

For respondents assigned to treatment group G2, the choice tasks looked similar to those shown to G1, however respondents were additionally required to indicate how they would reallocate their monthly household budget to account for any vehicle repayments required if they elected to purchase their preferred vehicle. Unlike the task in Study I, respondents were required to complete the budget reallocation for all four choice tasks. As with the task given to those assigned to group G1, respondents were also able to offset the vehicle purchase price by allocating any savings they had, therefore reducing the monthly repayments required to be made for their chosen vehicle. Figure 6 provides a screen capture of the task required for those assigned to treatment group G2. In the example shown, the household has indicated that they do not currently own a vehicle, hence they are not offered the opportunity to sell a vehicle to reduce their monthly repayments. For households with an existing vehicle, respondents were given the opportunity to sell the vehicle and hence reduce the required monthly repayments.

The final section of the survey involved collecting information on the socio-demographic characteristics of the respondent as well as about the size of the household. For consistency reasons, the same questions captured in the first survey were used in the second study.

3.1.1 Sample

A total of 998 respondents completed the second internet based survey. Respondents for the second study were drawn from an internet panel provided by PureProfile (www.pureprofile.com). The survey was conducted the week commencing the 9th December 2015. Eligible respondents, drawn from the population of Australia, had to be over 18 years of age and either have purchased a vehicle in the past 12 months or be currently in the market to buy a vehicle in the next 12 months, and not have taken part in the Study I survey conducted earlier that year. Respondents were asked at the commencement of the survey to provide information related to their average monthly spending for a range of typical household expenditure items, including savings (see Figure 1). Data from 27 respondents were removed during data cleaning as a result of providing what was considered to be nonsensical answers to the household expenditure question (e.g., spending zero dollars for food, or reporting a total expenditure that was less than their own net income levels), thus resulting in data from 971 respondents being available for use in the final analysis.



Vehicle Choice - Instructions

In the following screens you will be shown 4 scenarios, each displaying a number of hypothetical cars.

The cars will be described by a list of attributes, such as:

- General vehicle description (colour, body type, year of manufacture, odometer reading, fuel type, etc.)
- Car rating (performance and ride, and comfort and interior)
- Vehicle performance (air pollution rating, fuel consumption and noise data)
- Price

We would like you to consider the hypothetical cars on offer in each scenario and **select the vehicle you most prefer**. Once a vehicle is selected, you will be shown the minimum monthly repayments required for this vehicle. We would then like you to tell us whether you would actually choose to buy the car, or not buy the car. If you choose to buy the car, please adjust your monthly budget to accommodate the repayments for the car. You may also choose to use your savings to cover the full cost of the new car, or use some of your savings to reduce your monthly repayments. *Note - you may select a new vehicle from the available at any time.* Below is an example of the task.

EXAMPLE TASK

Please consider the cars on offer below and then select the vehicle you MOST prefer:

	Coupe	Stationwagon	Sedan	SUV	Convertible
Vehicle description					
Year of manufacture	2009	2009	2011	2008	2011
Odometer reading	107,640 km	80,616 km	45,228 km	105,196 km	58,016 km
Seating capacity	4 seats	4 seats	5 seats	4 seats	5 seats
Fuel type	Electric/petrol	Pure electric	Electric/petrol	Electric/petrol	Electric/petrol
Engine configuration	2 cylinder	0 cylinder	4 cylinder	4 cylinder	4 cylinder
Vehicle range (Km of travel on full charge)	N/A	290 km	N/A	N/A	N/A
Car rating					
Performance and ride					
Comfort and interior					
Vehicle performance					
Air pollution rating (1 - 10; 10 = No emissions)	6	10	7	7	6
Fuel consumption (Litres consumed per 100km)	1 L/100km	0 L/100km	4 L/100km	4 L/100km	1 L/100km
Stationary noise data (0 to 100; 0 = No noise)	50	0	60	60	50
Price					
Price	$ 10,900	$ 27,800	$ 21,200	$ 16,500	$ 9,400
Out of the cars shown, which is your MOST preferred vehicle?	○	○	○	○	◉

Your monthly repayments for the selected vehicle is:

Min Monthly repayments
$ 175.00

Please note you can select a new vehicle from above at any time

1. Would you:

○ Not buy the new car
◉ Buy the new car

2a. How much of your savings would you put towards the new car purchase?

(Note: you have $ 15,000 in savings)

$ 5000

2b. How would you change your monthly income allocation given your choice above?

	Average Monthly Income Allocation
Spending	
Entertainment	250.00
General household bills	350.00
Household groceries	300.00
Miscellaneous expenses	80.00
Rent/mortgage repayments	1000.00
Savings	500.00
Shopping (other than on groceries and household bills)	100.00
Transport/fuel	100.00
Childcare	0.00
Car repayments	80.00
Other (not specified above)	0.00
Borrow from family/friends	0.00
Total Average Monthly Income Allocation (For this scenario) $	2760.00
Total Average Income Allocation (Original) $	2680.00
Reduce your budget by $	80.00

Figure 6: Study II example choice screen with budget adjustment question

Upon recruitment, respondents were randomly assigned to one of two treatment groups (referred to as G1 and G2 throughout). Both treatment groups undertook the same SC experiment related to vehicle choice, however the second group where asked to complete questions about how they would reallocate their household budget based on their choices made. In this way, the first group acted as a control group, undertaking a survey similar to current practice involving SC experiments. A total of 498 respondents were assigned to treatment group G1, with the remaining 473 respondents allocated to treatment group G2. Table 2 provides a summary of the descriptive statistics of the socio-demographic breakdowns of the two samples. With the exception of gender, no statistical differences between the two treatment groups was found to exist. Whilst overall, females made up 43 percent of the data, a larger proportion of females relative to males were allocated to the second group, whilst a majority of males where sampled into the first group.

Table 2: Study 2 socio-demographic characteristics

	Overall sample	G1: No budget reallocation task	G2: Budget reallocation task
Respondent characteristics			
Age	46.16	46.50	45.81
Female (%)	0.43	0.32	0.54
Weekly income	$1,069.57	$1,021.60	$1,120.08
Respondent highest education level			
High school	0.29	0.32	0.26
Diploma	0.22	0.21	0.23
Bachelor's degree	0.28	0.27	0.30
Post graduate degree	0.17	0.16	0.18
Other	0.03	0.04	0.02
Employment class			
Full time student	0.06	0.06	0.05
Part time student	0.02	0.01	0.02
Employed full time	0.40	0.39	0.41
Employed part time	0.15	0.15	0.16
Employed casual	0.05	0.05	0.05
Not working for pay	0.01	0.01	0.01
Full time homemaker	0.08	0.08	0.08
Regular volunteer worker	0.01	0.01	0.01
Retired/Pensioner	0.19	0.20	0.18
Unemployed & seeking	0.02	0.02	0.01
Other	0.01	0.01	0.01
Household characteristics			
Num. of driver licences in HH	2.11	2.12	2.11
Num. of children in HH	2.11	2.11	2.11
Num. of adults in HH	0.58	0.57	0.58

3.2 Econometric model

All respondents, irrespective of whether they were assigned to treatment group G1 or G2, were asked to complete a series of discrete choice tasks involving the selection of their preferred choice of vehicle type out of the set shown. Respondents were first asked to indicate which vehicle they prefer the most, after which they could indicate whether they would likely purchase the vehicle or not, thus allowing for the possibility of not selecting any of the vehicles shown. For the current study, we concentrate on the unforced choice. In the current study, we estimate mixed multinomial logit (MMNL) models to explain the vehicle choice (including no choice). In making their vehicle selection, respondents were further able to elect to sell any vehicle they currently hold within their vehicle fleet mix, as well as use any savings they might have, so as to reduce the monthly payments required. The ability for respondents to affect the possible vehicle monthly repayments via the sale of one or more currently owned household vehicles or the use of any savings represents a possible source of endogeneity. To account for this possibility, we estimate Probit models to explain whether or not respondents choose to sell any of the existing household vehicles, and a Tobit model to model the amount of household savings allocated to reduce the price paid for their preferred vehicle. Endogeneity in the system of resulting equations is addressed via the inclusion of an additional correlated random term associated with each of the Probit, Tobit and MMNL models.

For those assigned to treatment group G2, respondents were further asked how they would reallocate their monthly household budget given the chosen vehicle in the SC experiment, noting no budget reallocation was necessary if none of the vehicles was selected. For this second treatment group, we estimate simultaneous with the MMNL, Probit, and Tobit models used to explicate vehicle choice, vehicle fleet change and use of any savings, a multiple discrete continuous extreme value (MDCEV) model to explain the observed budget reallocation task. In doing so, we allow for simultaneous feedback between the SC task and budget reallocation task, and the budget reallocation task and SC task. We explain each of the individual models, and the combined simultaneous estimation of all models, in the sections that follow.

3.2.1 Probit model: Accounting for vehicle fleet sales

Before undertaking the SC questions, respondents were asked to provide information for up to three vehicles that currently make up their household vehicle fleet, including data on vehicle age, the age at which the vehicle entered the household, the price of the vehicle at time of purchase, the vehicle make and model, engine size, etc. Based on the vehicle age and purchase price, respondents were provided with offers to sell one or more of their existing household vehicles in order to reduce the monthly cost associated with their choice of vehicle in each of the four SC scenarios. The offers for each vehicle were varied slightly in each task.

We model the choice as to whether or not a respondent elects to sell the l^{th} household vehicle, assuming the household currently owns one, using a series of binary Probit models. Let the utility for respondent *n* in choice task *t* associated with selling vehicle *l*, be

$$u_{ntl} = \theta v_{nl} + \sigma_v \eta_{n1} + \tau_{ntl}, \qquad (1)$$

where θ is a vector of parameters related to characteristics describing vehicle l=1,2,3, held by the household to which respondent *n* belongs, η_{n1} is a random term following a standard normal distribution which is correlated with similar random terms associated with the Tobit and MMNL models, σ_v represents a standard deviation parameter associated with the correlated random term, η_n^1, and τ_{ntl} is a random disturbance term, distributed $\tau_{ntl} \sim i.i.d.N(0,1)$.

Assigning a utility of zero to not selling vehicle *l*, the probability that respondent *n* will choose to sell the vehicle is given as

$$\begin{aligned} \Pr_{ntl}\left(u_{ntl} > 0\right) &= \Pr\left(\theta v_{nl} + \sigma_v \eta_{n1} + \tau_{ntl} > 0\right), \\ &= \int_{\eta^1}\int_{\tau} I_l\left(\theta v_{nl} + \sigma_v \eta_{n1} + \tau_{ntl} > 0\right)\varphi\left(\eta_{n1}\right)\phi\left(\tau_{ntl}\right)d\eta_{n1}d\tau_{ntl}, \end{aligned} \qquad (2)$$

where $I_l(.)$ is an indicator of whether the statement in parenthesis holds, and the integral is over all values of η_{n1} and τ_{ntl}.

Separate binary Probit models are estimated for each vehicle owned by a household, such that for any given respondent, there may exist between zero and three such models. Within respondent, each estimated binary choice model is correlated via the common random term, η_{n1}, with the parameter vector associated with the vehicle characteristics, θ, also held constant across each of the three possible models. The final model models the probability of observing the sequence of choices over choice tasks and vehicles. This choice probability shown in Equation (3), is

$$\Pr_n^* = E\left[\prod_{t}^{T=4}\prod_{l}^{L_n}\Pr_{ntl}^{Y_{ntl}}\right], \qquad (3)$$

where the expectation is over the random η_{n1} values, which make the probabilities $\Pr_{ntl}$ random, and Y_{ntl} is a binary variable equal to one if respondent *n* in choice task *t* chooses to sell vehicle *l*, or zero otherwise.

Whilst binary choice models are estimated only where a current household vehicle is present, for estimation purposes, the probability $\Pr_n^*$ is fixed to a value of one in cases where a household has zero vehicles present. In this way, the final system of modelled equations does not impact on the estimation of the parameters, θ or σ_v, but still allows for the specification of a fully integrated log-likelihood function over all modelled components. We discuss the reasoning for this further when we present the log-likelihood function for the final combined model.

3.2.2 Tobit model: Using existing savings

Respondents completing the SC task were able to reduce monthly repayments by offsetting the vehicle price paid with any savings they had accumulated in the past. To model the amount of savings allocated to the vehicle choice, we use a Tobit model. Allocation of savings in the model is treated as a latent variable which is explained via a linear function such that

$$S_{nt}^{*} = \kappa q_n + \eta_{n2} + \pi_{nt}, \tag{4}$$

where S_{nt}^{*} is the latent variable representing how much respondent *n* in choice task *t* uses in savings, including zero savings, κ is a vector of parameters associated with household socio-economic characteristics, q_n, η_{n2} is a random term following a standard normal distribution, which is correlated with random terms from the Probit and MMNL models, and π_{nt} is a random disturbance term, distributed $\pi_{nt} \sim i.i.d.N\left(0, \sigma_S^2\right)$.

Empirically, we observe the actual amount of savings allocated to the vehicle purchase rather than the latent variable, S_{nt}^{*}, such that

$$S_{nt} = \begin{cases} S_{nt}^{*} & \text{if } S_{nt}^{*} > 0 \\ 0 & \text{if } S_{nt}^{*} \leq 0, \end{cases} \tag{5}$$

where zero represents a natural censoring of savings used.

3.2.3 Base econometric model: Vehicle choice

In order to model the vehicle choice component of the survey, we make use of discrete choice models. Denote the utility of vehicle *j*, $j = 1, \ldots, J$, perceived by respondent *n* in choice task *t* as U_{ntj}. Utility is assumed to be comprised of a systematic component, V_{nsj}, and a random component, ε_{nsj},

$$U_{ntj} = V_{ntj} + \varepsilon_{ntj}. \tag{6}$$

The systematic component of utility, V_{ntj}, for vehicle *j* consists of a function $f_j(\cdot)$ of different attributes with levels $X = [x_{ntjk}]$ that characterise the alternative (and can somehow be observed or measured), and a set of weights or taste parameters, β,

$$V_{ntj} = f_j(x_{ntj}, \beta), \tag{7}$$

where $x_{ntj} \in R^K$ is a vector of attribute levels for vehicle *j* that define the alternative for respondent *n* in choice task *t*, and β is a vector of (unknown) parameters. The utility functions can essentially have any form, however, in most applications it is assumed that the utility is a linear combination of the attributes, such that we can write

$$V_{ntj} = \upsilon p_{ntj} + \sum_{k=1}^{K} \beta_k x_{ntjk}, \tag{8}$$

where we have separated out the price attribute, p_{ntj}, from the non-price attributes, such that υ is the parameter associated with price. Rather than use the vehicle price, p_{ntj} represents the minimum monthly repayments associated with vehicle *j*, after adjusting for the sale of any existing vehicle within the household fleet, as well as the use of any accumulated household savings.

The systematic component of utility may also include alternative-specific constants (ASCs), which may appear in the utility functions of a maximum $J-1$ alternatives. The modelling framework outlined above allows for presence of a no choice option, as is the case with the current study. The utility of the no choice alternative is void of attribute levels (e.g., there is no cost associated with not purchasing a vehicle), and hence, the no choice alternative can be assigned a utility of zero, or alternatively, have an ASC if the ASC of one of the other alternatives is normalised to zero.

Assuming independently and identically distributed (IID) EV1 random components, the probability of decision maker *n* choosing vehicle *j* in choice task *t* is,

$$P_{ntj} = \frac{\exp(V_{ntj})}{\sum_{i=1}^{J} \exp(V_{nti})}. \tag{9}$$

For the present study, we estimate mixed multinomial logit (MMNL) models, which allow for preferences to be treated as if they are heterogeneous over the population such that one or more parameters follow a certain probability distribution. As such, rather than assume fixed parameters β, we assume that β follows a given probability distribution with multivariate density $\phi(\beta \mid \Omega),$ where Ω is the vector of parameters of the distribution. For the models estimated herein, we assume that the random parameters are independently distributed, such that

$$\phi(\beta \mid \Omega) = \prod_{k=1}^{K} \phi_k(\beta_k \mid \Omega_k), \tag{10}$$

where $\phi_k(\beta_k \mid \Omega_k)$ is the univariate density function for parameter β_k. If a parameter β_k is assumed to be fixed instead of random, then $\phi_k(\beta_k) = 1.$

We further allow for the possibility of an error component within the utility framework adopted herein. The specification of an error component involves the nesting of alternatives into subgroups, which is achieved by the specification of a dummy variable, such that the dummy takes the value one if an alternative belongs to the subgroup, or zero otherwise. A normally distributed random parameter, with a mean of zero, is then associated with the dummy variable. Whilst econometrically an error component is no different to a traditional random parameter in terms of how it is estimated, the interpretation given to both types of parameters is somewhat different. Whilst a traditional random parameter is interpreted as the marginal utility associated with a particular level of the related attribute, x_{ntjk}, the fact that an error component is a random parameter that is common to subsets of alternatives, but not specific to any one attribute of the alternatives within that subset, means that it represent some unobserved correlated shift in the utilities of all alternatives to which it is assigned. Typically, the correlation of utilities within the subset of alternatives is interpreted as representing some form of substitution pattern between the set of nested alternatives. In the current study, we assign an error component to the utilities of the vehicles, such that they reflect a greater correlation of substituting choices between vehicles than with substituting a vehicle with the no-choice alternative. The utility function for each vehicle therefore becomes,

$$V_{ntj} = \upsilon p_{ntj} + \sum_{k=1}^{K} \beta_k x_{ntjk} + \sigma_b \eta_{n3}, \tag{11}$$

where is a random term distributed $\eta_{n3} \sim N(0,1)$, and σ_b represents the standard deviation of the error component.

As with the series of binary Probit models used to model the choice as to whether a respondent chooses to sell a vehicle or not, we model the probability of observing the sequence of choices each respondent makes over the *t* choice tasks in the SC component of the experiment. Let y_{ntj} be a binary variable equal to one if respondent *n* selects alternative *j* in choice task *t*, or zero otherwise. The probability, P_n^*, is observed to make a certain sequence of choices, is given by

$$P_n^* = E\left[\prod_{t}^{T=4} \prod_{j}^{J_t} P_{nsj}^{\;y_{nsj}}\right], \tag{12}$$

where the expectation is over the random term η_{n3}, which make the probabilities P_{nsj} random as well.

3.2.4 Handling endogeneity: correlated error terms

Given that respondents choosing to use existing household savings as well as sell existing household vehicles can potentially influence the minimum monthly payments required to be meet for each of the alternatives contained within the SC experiment, it is necessary to account for the possible existence of endogeneity bias when estimating the combined system of model equations (see Train 2009). To this end, we allow for correlated error terms to be estimated for each of the models associated with use of savings, the sale of existing vehicles, and the choice of vehicle in the SC tasks. The resulting multivariate Normal distribution is constructed from the univariate Normal distributions η_{n1}, η_{n2} and η_{n3}, such that

$$\begin{bmatrix}\eta_{n1}\\ \eta_{n2}\\ \eta_{n3}\end{bmatrix} : N\left(\begin{bmatrix}0\\0\\0\end{bmatrix},\begin{bmatrix}1 & \rho_1 & \rho_2\\ \rho_1 & 1 & \rho_3\\ \rho_2 & \rho_3 & 1\end{bmatrix}\right), -1 \le \rho_r \le 1, \forall r = 1,2,3. \tag{13}$$

The resulting Cholesky decomposition matrix for the variance-covariance term of Equation (13) is

$$\begin{bmatrix}1 & \rho_1 & \rho_2\\ \rho_1 & 1 & \rho_3\\ \rho_2 & \rho_3 & 1\end{bmatrix} = \begin{bmatrix}1 & 0 & 0\\ \rho_1 & a_1 & 0\\ \rho_2 & a_2 & a_3\end{bmatrix}\begin{bmatrix}1 & \rho_1 & \rho_2\\ 0 & a_1 & a_2\\ 0 & 0 & a_3\end{bmatrix} \tag{14}$$

where $a_1 = \sqrt{1-\rho_1^2}$, $a_2 = \left(\rho_1 - \rho_1\rho_2\right)/a_1$, and $a_3 = \sqrt{1-a_1^2-a_2^2}$, and where draws from this multivariate distribution are generated from independent $N(0,1)$ draws, r_1, r_2 and r_3 as follows.

$$\begin{aligned} r_{n1} &= r_1, \\ r_{n2} &= r_1\rho_1 + r_2 a_1, \text{ and} \\ r_{n3} &= r_1\rho_2 + r_2 a_2 + r_3 a_3. \end{aligned} \tag{15}$$

Whilst ρ_1 and ρ_2 are parameters to be directly estimated, ρ_3 is computed from the resulting Cholesky matrix. Given that ρ_3 is not directly estimated, we derive the standard error for this parameter using the Krinksy and Robb (1990) procedure.

3.2.5 MDCEV model: Household expenditure reallocation task

Respondents assigned to treatment group G2 were tasked with having to reallocate their monthly household budget subject to the repayment requirements given their choice in the related SC task. The budget reallocation task represents a form of multiple discreteness in which decision makers are required to simultaneously allocate continuous amounts of some type, in this case expenditure, towards two or more discrete outcomes, representing as budget expenditure items in the current study. To model these outcomes, we implement a version of Bhat's (2008) Multiple Discrete-Continuous Extreme Value (MDCEV) model, which is based on the Kuhn Tucker (1951) first-order conditions for constrained random utility maximization. The model assumes a generalised variant of constant elasticity of substitution (CES) direct utility function

$$U(\boldsymbol{x}_{nt}) = \sum_{c=1}^{C} \frac{\gamma_c}{\alpha_c}\psi_c \left\{\left(\frac{e_{cnt}}{\gamma_c}+1\right)^{\alpha_c} - 1\right\} \tag{16}$$

where $U(\boldsymbol{x}_{nt})$ is a quasi-concave, increasing, and continuously differentiable function with respect to the expenditure quantity (Cx1)-vector $\boldsymbol{e}$ ($e_{cnt} \ge 0$ for all c) associated with choice task s, and ψ_c, γ_c and α_c are parameters associated with budget item c.

ψ_c in Equation (16) represents the baseline utility, that being the marginal utility associated with zero expenditure, associated with expenditure item c, and in order for Equation (16)to be valid in an economic sense, must be greater than or equal to zero. Likewise, γ_c must also greater than zero for all c. The γ_c in Equation (16)assume several roles within the model framework. Firstly, γ_c shifts the point at which the indifference curves are asymptotic to the axes representing different amounts of expenditure between budget items. Secondly, γ_c allows for the possibility of corner solutions in terms of allocation amongst the C expenditure items. Finally, the value of γ_c impacts on the steepness of the indifference curve in the positive orthant, and as such γ_c further acts as a satiation parameter, such that the higher the value of γ_c, the less the satiation effect on the expenditure on item c. Unlike γ_c, α_c has but a single role to play in terms of its impact on the interpretation of Equation (16). Taking a value less than or equal to 1, α_c acts as a satiation parameter, similar to the third role of γ_c. A value of $\alpha_c = 1$ implies no satiation effect, whilst as $\alpha_c \to -\infty$, the model implies immediate satiation related to expenditure item *c* (see Bhat 2008) for a more detailed explanation of the role each of these parameters play in terms of the MDCEV model and its interpretation.

The MDCEV model allows for the baseline utility for each expenditure item ψ_c, to be parameterised such that

$$\psi_c = \exp(\xi_c z_{cn}), \tag{17}$$

where Z_{cn} is a vector of attributes characterizing expenditure alternative *c,* and may include a constant for *C*-1 ψ functions, or represent potentially characteristics of the decision maker *n,* and ξ_c is a vector of parameters to be estimated. The exponential in Equation (17) ensures that $\psi \geq 0$.

In operationalising the model, so as to ensure $\alpha_c \leq 0$, α_c is parameterized as $[1-\exp(-\delta_c)]$, where δ_c is the parameter to be estimated. Further, to allow the satiation parameters (*i.e.*, the α_c values) to vary across individuals, Bhat (2005) specifies $\delta_{cn} = \omega'_c h_{cn}$, where h_{cn} is a vector of individual characteristics impacting satiation for the c^{th} alternative, and θ_c is a corresponding vector of parameters. Given $\gamma_c > 0$, γ_c is re-parametrising as $\exp(\varpi_c)$. Additionally, the translation parameters can be allowed to vary across individuals by specifying $\varpi_{cn} = \varphi_c' v_{cn}$, where v_{cn} is a vector of individual characteristics for the c^{th} alternative, and φ_c is a corresponding vector of parameters.

As noted by Bhat (2008), γ_c and α_c both act as satiation parameters and as such it is rarely possible to empirically identify both parameters simultaneously. Bhat (2008) therefore recommends to estimate either γ_c or α_c but not both. In the case where γ_c is estimated, resulting in a model known as $\gamma-$profile, the analyst normalises $\alpha_c = 0, \forall c.$ The $\alpha-$profile version of the model, involves estimation of α_c and the normalisation of $\gamma_c = 1, \forall c.$ In the current study, we estimate the $\gamma-$profile version of the MDECV model.

Solving the optimal expenditure allocations by forming the Lagrangian and applying the Kuhn-Tucker conditions, Bhat (2008) shows that the utility associated with expenditure item *c* in choice task *s*, is given as

$$\begin{aligned} W_{cnt}^* &= \lambda \xi' z_{cn} + (\alpha_c^* - 1)\ln\left(\frac{e_{cnt}^*}{\gamma_c p_{cnt}} + 1\right) - \ln p_c, \quad (c = 1, 2, ..., C) \\ &= \lambda \xi' z_{cn} + \sigma(\alpha_c - 1)\ln\left(\frac{e_{cnt}^*}{\gamma_c p_{cnt}} + 1\right) - \ln p_c, \ (c = 1, 2, ..., C), \end{aligned} \tag{18}$$

where γ_c, α_c, ξ and z_{cn} are as per previously defined, e_{cnt}^* is the optimal expenditure allocation associated with item *c*, and p_{cnt} is the price per unit associated with expenditure item *c*, as made by respondent *n* in choice task *t*. λ in Equation (18) is a scale parameter which in the current study we normalise to 1.0. Given the price per unit is equal to one for all expenditure items, and adopting a $\gamma-$profile, Equation (18) collapses to

$$W_{cnt}^* = \xi' z_{cn} - \ln\left(\frac{e_{cnt}^*}{\gamma_c} + 1\right), \ (c = 1, 2, ..., C). \tag{19}$$

For choice task *s*, the probability of a given consumption vector $\left(e_{1nt}^*, e_{2nt}^*, e_{3nt}^*, ..., e_{M_{nt}}^*, 0, 0, ..., 0\right)$, where *M* of the *C* expenditure items has expenditure greater than zero, is given as

$$\text{Prob}_{nt}\left(e^*_{1nt}, e^*_{2nt},\ e^*_{3nt},\ ...,\ e^*_{M_{nt}},\ 0,\ 0,\ ...,\ 0\right)$$

$$= \left[\prod_{c=1}^{M_{nt}} g_{cnt}\right]\left[\sum_{c=1}^{M_{nt}} \frac{1}{g_{cnt}}\right]\left[\frac{\prod_{c=1}^{M_{nt}} e^{W_{cnt}}}{\left(\sum_{c=1}^{C} e^{W_{cnt}}\right)^{M_{nt}}}\right](M_{nt}-1)!, \tag{20}$$

where $g_{cnt} = \left(\dfrac{1-\alpha_c}{e^*_{cnt} + \gamma_c p_{cnt}}\right)$ which collapses to $g_{ct} = \left(\dfrac{1}{e^*_{cnt} + \gamma_c}\right)$ under the $\gamma-$profile of the model, assuming unit prices.

A further point of clarification about the MCDEV model specification used here is necessary. At the outset of the survey, we capture the household monthly expenditure for all items *c*, save for the car repayments item, which by design are specific to each of the four SC task questions. Within the modelling process, we include this base revealed preference (RP) expenditure pattern alongside the observed expenditure patterns associated with the four SC tasks such that T =5 rather than four for the MCDEV model. For the RP expenditure observation, no SC car repayments are observed, and hence $e^*_n = 0$ for this observation.

3.2.6 Combining the vehicle choice model with the MDCEV model: Allowing for feedback relationships

Respondents assigned to treatment group, G2, were asked to first make a choice between a finite number of vehicles shown in a SC experiment, including a no choice option, after which depending on their response, they were asked to indicate how they would reallocate their monthly household budget to account for any repayments necessary given their aforementioned choice. These monthly repayments could potentially be reduced if the respondent indicated that they would allocate existing savings to offset the purchase of the vehicle, or similarly use money obtained from the sale of existing household vehicles. The overall task allowed respondents to change their vehicle choice so as to explore the implications on the household budget as well as make changes to their existing vehicle fleet. To accommodate the complex choice process of the survey task, we hypothesis a model framework in which the utility derived from the vehicle choice impacts upon the sub component of utility associated with the vehicle repayment expenditure category within the household budget reallocation task, such that a greater level of utility derived from a chosen vehicle will result in a higher expenditure on repayments for the vehicle within the household budget. We further hypothesis that as the utility associated with non-car repayment expenditure categories increase, respondents are more likely to choose none of the vehicles in the SC experiment given that these expenditure items represent competing outside goods in terms of possible household budget allocation.

To accommodate the influence of the vehicle choice on the allocation of household expenditure towards possible vehicle repayments, we compute the expected maximum utility (EMU), given as the familiar log-sum formula, for all alternatives *j* in the SC task save for the no choice alternative. We ignore the no-choice alternative in the EMU calculation, given our assumption that the relationship between the no choice alternative and the budget allocation task exists for all non-car repayment expenditure categories, rather than the repayment allocation category itself. The EMU for choice respondent *n* in task is given in Equation (21).

$$EMU_{nt} = \ln \sum_{j=1}^{J} e^{V_{ntj}}, \quad \forall j, j \neq none. \tag{21}$$

The EMU from Equation (21) enters into the utility for the car repayment expenditure item such that Equation (19) for this item becomes

$$W_{repay,nt} = \xi' z_{repay,nt} + \tau EMU_{nt} - \ln\left(\frac{e^*_{repay,nt}}{\gamma_{repay}} + 1\right), \tag{22}$$

where τ is a parameter to be estimated, reflecting the influence of the vehicle choice EMU on the utility associated with the car repayment expenditure item.

It is worth noting that the inclusion of the EMU into the car repayment sub-utility function associated with observations related to the SC questions, means that the MCDEV model contains indirectly random parameter terms. As with the treatment of the other modelled probabilities, we model the sequence of choice probabilities over the *t* observations. Given the common set of draws, we estimate the sequence of choice probabilities over the SC model and MCDEV model simultaneously. As such, the choice probability for the joint model becomes

$$\text{Prob}_n^* = E\left[\prod_t^{T=4}\prod_j^{J_t} P_{nsj}^{\;y_{nsj}} \prod_t^{T=5}\text{Prob}_{nt}\right], \tag{23}$$

where the expectation is over the random terms introduced via Equation (22).

The feedback loop between the budget reallocation task and the SC questions is completed via the inclusion of the MCDEV sub-utilities for the non-car repayment expenditure categories into the utility function of the no choice alternative of the SC model, as shown in Equation (24)

$$V_{nt,no} = \vartheta + \Psi W_{cnt}, \quad \forall c \neq \text{car repayments}, \tag{24}$$

where ϑ is an ASC associated with the no choice alternative, and Ψ is a vector of parameters associated with W_{cnt}.

3.2.7 Estimating the model: Log-likelihood function

The presence of random parameters requires that the choice probabilities of the model be integrated over the random parameter distribution assumed. Unfortunately, this represents an intractable problem from an analytical perspective, which in practice is most commonly solved by use of simulation methods. This involves taking multiple draws from the random parameter distribution and calculating the expectation of the choice probability over the draws. A simulated maximum likelihood estimator is therefore used to maximise the log-likelihood function of the model based on the expected choice probabilities. Likewise, the presence of a random term within the Tobit model regression function means that it is necessary to use a simulated maximum likelihood estimator for the Tobit model.

In order to estimate the parameters κ and σ_S, simulated maximum likelihood function for the Tobit model is given as

$$\ln L_n^1 = E\left[\sum_{S_{nt}=0}\ln\left[1-\Phi\left(\frac{\kappa q_n + \eta_{n2}}{\sigma_s}\right)\right] + \sum_{S_{nt}>0}\ln\left[\frac{1}{\sigma_s}\phi\left(\frac{S_{nt}-\kappa q_n - \eta_{n2}}{\sigma_s}\right)\right]\right], \tag{25}$$

where $\Phi(.)$ is the inverse the cumulative distribution function of a standard normal distribution, and $\phi(.)$ is the corresponding density function, and the expectation is over the random term η_{n2}.

The overall simulated likelihood function for the entire model system, assuming choice probabilities given in Equations (3), (12) and (23), combined with the simulated log-likelihood function for the Tobit model, is given as

$$LnL_M = \sum_{n=1}^{N}\left[\ln\left(\text{Pr}_n^*\,\text{Prob}_n^*\right) + \ln L_n^1\right]. \tag{26}$$

As noted previously, for households without an existing vehicle, it is necessary to set $\text{Pr}_n^* = 1$, else the term $\text{Pr}_n^* P_n^* \text{Prob}_n^*$ will equal zero, and the simulated log-likelihood function of the model will no longer be defined. We further note that for respondents assigned to treatment group G1 were not required to complete the budget reallocation task, and hence for these respondents, Prob_n^* does not appear in the log-likelihood function for this group. Further, only 11 respondents in treatment group G1 indicated in 16 choice tasks that they would use existing savings to decrease the vehicle repayments. Unfortunately, this small number of observations does not allow for estimation of the

Tobit model component for this group, and as such, the simulated log-likelihood function for this group collapses to

$$LnL_M = \sum_{n=1}^{N} \ln\left(\Pr_n^* P_n^*\right). \tag{27}$$

All models are estimated using Python Biogeme 2.4 (Bierlaire 2016). Ten thousand Modified Latin Hypercube Sampling (MLHS) pseudo random draws (see Hensher et al. 2015) were used in estimating the simulated log-likelihood function of the models.

3.3 Results

Table 3 presents the results of two models, one for each treatment group, G1 and G2. As noted in the previous section, there exists insufficient observations to model the use of savings to decrease the vehicle repayments for treatment group G1. For treatment group G2, 154 respondents in 290 choice tasks suggested they would use existing savings to reduce vehicle repayments, which provides sufficient data to model this outcome. The large negative constant for the Tobit model associated with treatment group G2 supports the observation that the vast majority of respondents choose not to use existing savings when considering purchasing a new vehicle. After extensive testing, the weekly income of the respondent and number of children in a household were found to be statistically significant in determining how much savings would be employed to reduce overall vehicle repayments. The positive parameter associated with weekly income suggests that higher earning respondents are more likely to use a greater amount of savings to offset the purchase price of a vehicle in the SC tasks, likely the result of such individuals having a larger sum of savings available to do so. The positive parameter associated with the number of children resident within a household suggests that families with more children are more likely to use larger amounts of existing savings to reduce vehicle repayments for newly purchased vehicles. We hypothesis that by reducing vehicle repayments by using savings to reduce the principle owing on a newly purchased vehicle, households with more children have access to greater discretionary income which provides greater flexibility in monthly expenditure patterns.

The second section of Table 3 reports the results from the series of Probit models used to model the probability that respondents will sell vehicles from their existing household fleet in order to subsidise the purchase of a new vehicle in the SC tasks. For both treatment groups, there exists a statistically significant negative constant, suggesting that, *all else being equal*, respondents are unlikely to sell an existing vehicle as a replacement for a new vehicle within the SC tasks. This effect appears to be much more pronounced for those assigned to treatment group G2, than for those belonging to the first treatment group. For treatment group G1, the number of vehicles that currently belong to a household as well as the square root of the age each of the vehicles were found to explain whether or the vehicle would be sold or not. For treatment group G2, only the square root of the age each of the household vehicles was found to be statistically significant. Other variables tested, including socio-demographic characteristics of the respondent, the characteristics of the household, and additional attributes of the existing vehicle were not found to influence this choice. Surprisingly, for treatment G1, the number of vehicles currently owned by a household was found to be negatively related to respondents indicating they would sell the vehicle. This suggests that by and large, the sample would prefer to increase the size of their current vehicle fleet holdings rather than use the purchase of an additional vehicle as a replacement vehicle. As is to be expected, for both samples, older vehicles are more likely to be replaced than newer vehicles, *all else being equal*.

The next two sections of Table 3 present the results for the vehicle choice experiment. First to be presented are the parameters associated with the vehicle attributes, after which the parameters related to the no-choice alternative are reported, including feedback parameters from the MCDEV model for treatment group G2. Models for both samples involve estimation of a series of random and fixed parameters. With the exception of the price parameter, all random parameters are assumed to be normally distributed. For the price parameter, the parameter is assumed to follow a negative lognormal distribution. Different preference structures are observed for the two samples with regards to vehicle colour. For sample G1, there exists significant preference heterogeneity for blue coloured vehicles, however on average there appears to be no preference either for or against blue cars. No other vehicle colour effects were found for this sample. For sample G2 however, there is found to exist significant preference heterogeneity associated with green, red, and silver coloured vehicles, with a statistically significant negative average preference being observed against red and silver vehicles, but with no average effect against green coloured vehicles. Blue coloured vehicles were not found to have an influence, either positive or negative on the choice of vehicle.

Table 3: Study II results

	G1: No budget				G2: Budget with MDCEV			
	Mean par.		Std Dev. par.		Mean par.		Std Dev. par.	
Name	**Par.**	**(*t*-test)**	**Par.**	**(*t*-test)**	**Par.**	**(*t*-test)**	**Par.**	**(*t*-test)**
Savings: Tobit Model								
Constant	-	-	-	-	-16,305.800	(-13.23)	-	-
Number of children in HH	-	-	-	-	1,423.170	(3.49)	-	-
Weekly income	-	-	-	-	2.107	(3.18)	-	-
Sigma (σ_s)	-	-	-	-	12,465.200	(20.53)	-	-
Sale of existing vehicle fleet: Probit Model								
Constant	-1.414	(-7.86)	-	-	-2.049	(-16.69)	-	-
Age of vehicle	0.377	(9.74)	-	-	0.253	(6.38)	-	-
Number of vehicles in HH fleet	-0.501	(-5.51)	-	-	-	-	-	-
Sigma (σ_v)	-1.414	(-7.86)	-	-	1.000	-	-	-
Stated choice experiment: vehicle choice parameters								
Vehicle colour: Blue	-0.227	(-0.99)	1.384	(3.11)	-	-	-	-
Vehicle colour: Green	-	-	-	-	-0.570	(-1.46)	1.729	(3.38)
Vehicle colour: Red	-	-	-	-	-1.078	(-2.04)	2.166	(3.23)
Vehicle colour: Silver	-	-	-	-	-1.161	(-1.91)	2.620	(3.52)
Vehicle type: Coupe	0.095	(0.44)	0.841	(1.74)	-0.677	(-1.49)	2.619	(5.15)
Vehicle type: Hatchback	-	-	-	-	-0.548	(-2.16)	-	-
Vehicle type: Sedan	0.612	(4.27)	-	-	-	-	-	-
Vehicle type: Station wagon	-	-	-	-	-2.667	(-3.11)	3.479	(4.25)
Vehicle type: SUV	0.630	(4.23)	-	-	-	-	-	-
Vehicle type: Ute	-1.425	(-2.77)	2.268	(4.09)	0.153	(0.43)	2.287	(4.27)
Comfort rating	0.094	(2.54)	-	-	-0.021	(-0.25)	0.584	(5.00)
Diesel fuel	-0.227	(-1.77)	-	-	-0.343	(-1.08)	1.916	(4.41)
Num. of Cylinders	-0.024	(-1.12)	0.104	(2.52)	0.036	(1.05)	0.179	(2.38)
Number of seats	0.111	(2.42)	-	-	0.163	(2.42)	-	-
Odometer	-0.068	(-3.60)	0.107	(3.27)	-0.277	(-5.25)	0.357	(6.05)
Performance rating	0.145	(3.85)			0.084	(1.16)	0.422	(3.01)
Pollution rating	-	-	-	-	0.099	(1.65)	0.185	(3.19)
Price	-4.485	(-33.57)	2.158	(12.69)	-5.125	(-30.32)	1.383	(7.57)
Error component (σ_b)	-	-	1.101	(3.65)	-	-	3.145	(5.98)
Stated choice experiment: No choice parameters								
Constant (no choice)	-0.707	(-2.62)	-	-	3.235	(3.96)	-	-
W(Entertainment)					-0.019	(-0.67)	0.06	(1.75)
W(Miscellaneous)	-	-	-	-	-0.039	(-1.47)	0.06	(2.55)
W(Rent/mortgage)	-	-	-	-	-0.072	(-2.31)	0.13	(2.43)
Endogeneity correlation parameters								
ρ(Probit,Tobit)	-	-	-	-	0.352	(6.12)	-	-
ρ(Probit,SC)	-0.465	(-2.93)	-	-	0.638	(1.99)	-	-
ρ(Tobit,SC)*	-	-	-	-	0.352	(4.64)	-	-
MDCEV model								
Sub utility functions ψ_c								
ASC Entertainment	-	-	-	-	-2.998	(-13.11)	-	-
Num. children in HH - entertainment	-	-	-	-	-0.203	(-7.60)	-	-
ASC General household bills	-	-	-	-	-1.607	(-6.68)	-	-
ASC Miscellaneous	-	-	-	-	-3.077	(-13.46)	-	-
Num. children in HH - Miscellaneous	-	-	-	-	-0.068	(-2.59)	-	-
ASC Rent/mortgage	-	-	-	-	-4.064	(-17.03)	-	-
Num. adults in HH rent/mortgage	-	-	-	-	-0.152	(-4.43)	-	-
Num. children in HH - rent/mortgage	-	-	-	-	0.120	(4.62)	-	-
ASC Savings	-	-	-	-	-3.969	(-17.42)	-	-
Num. children in HH - savings	-	-	-	-	-0.085	(-3.14)	-	-
ASC general shopping	-	-	-	-	-2.992	(-13.08)	-	-
Num. children in HH - general shopping	-	-	-	-	-0.191	(-6.96)	-	-
ASC Transport	-	-	-	-	-2.046	(-8.76)	-	-
ASC Other expenditure	-	-	-	-	-5.021	(-20.18)	-	-
Num. adults in HH -other	-	-	-	-	-0.091	(-1.99)	-	-
Num. children in HH - other	-	-	-	-	-0.066	(-1.77)	-	-
ASC Vehicle repayments	-	-	-	-	-7.354	(-17.43)	-	-
τ(EMU)	-	-	-	-	0.463	(8.32)	-	-

Table 3 Study II results (cont'd)

MDCEV model								
Gamma functions (Υ_c)								
ASC Entertainment	-	-	-	-	3.755	(35.84)	-	-
Age - entertainment	-	-	-	-	-0.011	(-5.24)	-	-
ASC General household bills	-	-	-	-	2.243	(17.28)	-	-
Age - general bills	-	-	-	-	0.011	(6.18)	-	-
Female - general bills	-	-	-	-	0.175	(3.43)	-	-
ASC Groceries	-	-	-	-	1.408	(6.16)	-	-
ASC Miscellaneous	-	-	-	-	3.515	(63.20)	-	-
Female - miscellaneous	-	-	-	-	-0.140	(-2.34)	-	-
ASC Rent/mortgage	-	-	-	-	6.540	(87.06)	-	-
Female - rent/mortgage	-	-	-	-	0.221	(2.40)	-	-
ASC Savings	-	-	-	-	5.581	(38.80)	-	-
Age - savings	-	-	-	-	-0.008	(-2.85)	-	-
Female - savings	-	-	-	-	-0.558	(-7.02)	-	-
ASC General shopping	-	-	-	-	3.469	(61.80)	-	-
Female - general shopping	-	-	-	-	-0.135	(-2.25)	-	-
ASC Transport	-	-	-	-	2.464	(35.68)	-	-
ASC Other expenditure	-	-	-	-	5.160	(65.43)	-	-
Female - other expenditure	-	-	-	-	-0.278	(-2.52)	-	-
ASC Vehicle repayments	-	-	-	-	5.617	(15.57)	-	-
Age - vehicle repayment	-	-	-	-	-0.017	(-2.10)	-	-
Model fit								
LL(0)	-3664.762				-180,883.622			
LL(β)	-2869.328				-116,120.118			
ρ^2	0.217				0.358			
adj. ρ^2	0.177				0.223			
Num. par.	24				82			
Sample size	498				473			

* Standard error computed using Krinsky and Robb (1990) procedure

For treatment group G1, on average, respondents display a statistically significant preference against purchasing a ute relative to other vehicle body types, and a statistically significant preference for buying either a sedan or SUV. There exists for this group however, significant preference heterogeneity towards the purchase of both utes and coupes. In contrast, on average there exists no impact on utility for respondents belonging to treatment group G2 for utes, SUVs or sedans, and a negative overall preference towards coupes relative to other vehicle body types, although there does also exist statistically significant preference heterogeneity for both utes and coupes within this sample. Further, respondents assigned to treatment group G2 are observed to have a negative overall preference towards hatchbacks and station wagons, when no such effects are observed within treatment group G1.

Treatment group G1 has statistically significant fixed positive parameter estimates for vehicles with higher comfort and performance ratings, whilst for treatment group G2, whilst no statistically significant mean effect was found for these two attribute, significant preference heterogeneity was detected. For diesel fuelled vehicles, a fixed negative parameter was found to be marginally statistically significant for treatment group G1, whilst for treatment group G2, only the standard deviation parameter for this attribute is statistically significant, indicating significant preference heterogeneity for this variable. For both treatment groups, a fixed positive parameter was found to be statistically significant for the number of seats attribute, whilst for both groups, significant heterogeneity was found to exist for the number of cylinders attribute. Combined, this suggests that respondents tend to prefer larger vehicles but are heterogeneous in terms of their preferences for either vehicles with smaller or larger engines, all else being equal. Overall, the two models also suggest that both groups also were found to have a negative mean parameter for the odometer reading attribute, as well as statistically significant standard deviation parameters. The significant heterogeneity parameters for the odometer reading attribute can be interpreted as reflecting different preferences for newer or older vehicles, given this attribute was correlated with the vehicle age in the experiment. Interestingly, the pollution rating was found to not influence vehicle choice for treatment group G1, and whilst the mean parameter associated with the pollution rating of vehicles on offer was not statistically significant for group G2, the standard deviation parameter was. This suggests that on average, respondents belonging to the second treatment group displays, on average, neither a taste nor distaste for less polluting vehicles, however significant preference heterogeneity is evident for this attribute for group G2.

Also reported in the table are the population moments of the underlying normal distribution associated with the lognormally distributed price parameters. Converting the parameters for the underlying distribution to that of the lognormal, the mean, median and standard deviation of preferences associated with the price attribute for group G1 are -0.111, -0.011 and 0.667 respectively, and -0.015, -0.006 and 0.0034 for treatment group G2. Whilst a direct comparison between the two results should be avoided due to potential differences in scale between the two data sets, this finding suggests that respondents completing both the SC task and budget reallocation task have a much lower sensitivity to price than those who were asked only to complete the SC task. With regards to scale, it is worth noting that for the non-price mean parameter estimates that are statistically significant across both treatment groups, parameters for the model that are estimated on the data collected from the second group are a median 2.77 times larger than those estimated for the first group. For the heterogeneity parameters, the parameters from the second group are a median 2.42 times larger than those from the first. Whilst not offered as formal proof of the existence of scale differences between the two data sets, this finding does suggest that scale differences do exist between the two data sets, with scale being larger in the second data set. Assuming this to be the case, it is particularly noteworthy that the price parameter is much lower for treatment group G2 than for treatment group G1.

To rule out experimental design influences being the source of the observed difference in the magnitude of the price parameters, Table 4 details the average and median monthly repayments for treatment groups G1 and G2 over the experiment. Shown in the table are the original average and median monthly repayments shown to respondents from both groups, as well as the average and median monthly repayments respondents saw after adjusting for the use of any savings and the sale of existing household vehicles. Repayments are further broken down into values for all vehicles shown to respondents, versus monthly repayments for the chosen vehicle only. Visual examination of the table shows that there exists an $8.84 difference in the vehicle prices originally displayed to respondents across the two data sets ($718.78 versus $709.94), which decreases to a $0.50 difference after accounting for price adjustments resulting from the use of savings and from the sale of existing ($640.70 versus $641.20).

Table 4: Vehicle repayment values

	Original vehicle monthly repayment	Vehicle monthly repayment after adjustment
G1	*All vehicles*	
Average	$718.78	$640.70
Median	$580.00	$515.00
	Chosen vehicle	
Average	$571.22	$488.72
Median	$505.00	$350.00
G2	*All vehicles*	
Average	$709.94	$641.20
Median	$570.00	$520.00
	Chosen vehicle	
Average	$546.35	$482.16
Median	$482.50	$430.00

Considering just the chosen vehicle, even after adjusting for respondents offsetting the vehicle price with the use of savings and money earned from selling vehicles from their existing fleet, average differences in the monthly repayments between the two groups is not large ($488.72 compared to $482.16), however a much larger discrepancy is observed in terms of the median price difference between the two groups ($350.00 versus $430.00). The large difference between the average and median prices for the chosen vehicle after adjusting for selling existing household vehicles, suggests a somewhat skewed price distribution for group G1. Overall however, it is apparent that the observed differences in the magnitudes of the price parameters between the two groups is not the result of systematic differences in the application of the experiment design as applied to the two groups. Our findings therefore suggest, that even accounting for possible scale differences, the observed difference in the marginal utility for price is the result of differences in preference between the two groups, and not due to some experimental artefact resident within the data.

A further point of departure between the models obtained from the two groups lies in the relative magnitudes of the error component parameter estimates. Whilst the median standard deviation parameter for G2 is 2.42 times that observed for G1 given non-price attributes, the error component parameter for G2 is 2.86 times larger in magnitude than that obtained from treatment group G1. This suggests, all else being equal, that when chosen, there exists substantially more substitution occurring between vehicles for treatment group G2 than for G1. A further point of difference between the two models exists with the no-choice ASC parameter, with a statistically significant negative parameter being estimated for treatment group G1, whilst treatment group G2 is observed to have a statistically significant positive ASC for the same no-choice option. This later finding indicates that respondents not having to perform the budget reallocation task were more likely to select a vehicle than not, *all else being equal*, whilst respondents who had to complete the budget reallocation task, tended more often to choose the no-choice alternative, *ceteris paribus*.

Also included in the utility function of the no choice alternative of treatment group G2 are the sub-utilities for three household expenditure items derived from the budget reallocation task MCDEV model. After extensive testing, it was found that the sub-utilities for entertainment, miscellaneous spending, and rent/mortgage act to explain the choice of the no-purchase option in the SC experiment. Random parameters following univariate normal distributions were estimated for each of the three sub-utilities, resulting in statistically significant negative mean parameter estimate for the rent/mortgage MCDEV sub-utility. We interpret this finding as suggesting that as the utility of a respondent increases for putting money towards rent/mortgage, they are more likely to also purchase one of the vehicles present within the SC task, *all else being equal*. This finding suggests that within the confines of the experiment conducted, on average, rent/mortgage payments act as an economic compliment to the purchase of a new vehicle, *ceteris paribus*. Nevertheless, there does exist significant preference heterogeneity for this as well as the entertainment and miscellaneous spending sub-utility functions, in relation to their impact on the no-choice alternative. Such heterogeneity suggests that for some of the sample, respondents who experience increasing utility for expenditure within these categories view the purchase of a vehicle as a compliment, whilst others within the sample view such a purchase as a direct economic alternative.

The fourth section of Table 3 presents the results of the correlated error terms tying the Probit, Tobit and MNNL models together. Given it was not possible to estimate a Tobit model for treatment group G1, only the correlation for the Probit and MMNL model error terms are presented within the table for this group. For treatment groups G1, a statistically significant and negative correlation parameter is estimated to exist between the series of Probit models used to explain the sale of existing vehicles from a households fleet, and the MMNL model used to explain the choice of vehicle in the SC experiment. Following Train (2009), we interpret this finding as suggesting that the unobserved effects explaining whether or not a respondent sells an existing vehicle is negatively related to the respondent's preference for purchasing a new vehicle in the SC experiment, *ceteris paribus*. The opposite effect however is observed for treatment Group G2. This suggests that for this sample, the unobserved effects explaining whether or not a respondent sells an existing vehicle is negatively related to the respondent's preference for purchasing a new vehicle in the SC experiment, *all else being equal*. For the second treatment group, we found a statistically significant and positive correlation parameter for the error terms of the Probit and Tobit models. This suggest, *ceteris paribus*, that the unobserved effects explaining whether a respondent sells an existing vehicle are positively correlated with the unobserved effects that explain how much savings they are prepared to use to offset the vehicle price in the SC experiment. As such, (un)desirable unobserved effects explaining the sale of existing vehicles are likely to play a similar role with regards to the (un)desirable unobserved effects that help explain how much household savings respondents put towards the SC vehicle of choice. Likewise, a positive and statistically significant correlation is observed to exist between the error terms of the Tobit model and MMNL model.

The next two sections of Table 3 report the parameter estimates associated with the MCDEV budget expenditure model. First to be reported are the parameters associated with the sub-utilities for nine of the 12 expenditure categories. The category of childcare was excluded from the analysis due to an insufficient number of respondents reporting positive expenditure for this budget item. Borrowing from family and friends was excluded for similar reasons. Utility for expenditure on grocery items was normalised to zero for identification reasons, such that the utility functions for the remaining budget category items can be interpreted relative to this category. The ASCs for the remaining nine budget categories are statistically significant and negative, suggesting that *all else being equal*, relative to grocery shopping, expenditure on these items is less preferred. The model suggests that increasing the number of children in a household tends to result in lower expenditure on entertainment, savings, general shopping, and miscellaneous and other expenses, *ceteris paribus*, but increases expenditure on rent/mortgage payments. Increasing the number of adults in a household however tends to result in lower expenditure on rent/mortgage payments, but also reduces expenditure on other expenses, *all else being equal*. As is to be expected, the model predicts that as the EMU derived from the SC experiment increases, expenditure on vehicle repayments also increases, supporting the hypothesis that individuals are willing to pay more for a vehicle that they will derive a greater degree of utility for owning.

Within the model framework, the γ_c parameters have been estimated as a function of socio-demographic variables. These parameters are shown in the sixth section of Table 3. Negative parameters were found for female respondents for the γ_c parameters associated with the expenditure categories of savings, general shopping, and miscellaneous and other expenses, and positive parameters for general household bills and rent/mortgage payments. Age was found to be negatively associated with the γ_c parameters of entertainment, savings, and vehicle repayments, and positively related with general household bills. Rather than offer an interpretation of these results here, we demonstrate how these parameters affect the results within the context of the entire model system in the next section.

3.4 Example application of model

In this section, we demonstrate via a hypothetical case study, firstly, how the predicted model outcomes differ depending on whether one applies the model estimated using just the SC experiment based on treatment group G1 versus whether one where to operationalise the full model framework associated with treatment group G2, and secondly, to show how the second model can be used to demonstrate the link between the SC experiment and the other outside goods represented by the budget reallocation task. To do so, consider three distinct decision makers belonging to family units described by different household characteristics, with different spending patterns. Further, consider that each decision maker is confronted with the choice of purchasing a vehicle from different and unique markets. Table 5 summarises the relevant characteristics of each decision maker, the attributes of the households to which they belong, and the vehicles that are present within the market to which each person is confronted with. For simplicity, assume that the monthly repayments for the various vehicles shown are the repayments required after adjusting for the use of any previous acquired savings, as well as the sale of any existing household own vehicle.

Table 5: Person, household and vehicle characteristics

	Person and household characteristics								
	Person #1			**Person #2**		**Person #3**			
Gender	Female			Female		Male			
Age	36			28		58			
Weekly Income	$1,000			$1,200		$900			
Number of Adults in HH	2			1		2			
Number of Children in HH	1			0		3			
Number of Vehicles in HH	2			1		0			
Age of Vehicle #1	2			8		-			
Age of Vehicle #2	6			-		-			
HH budget for entertainment	**$200 / month**			**$350 / month**		**$250 / month**			
HH budget for rent/mortgage	**$2000 / month**			**$2500 / month**		**$1500 / month**			
	Vehicle attributes								
	Car(1)	**Car(2)**	**Car(3)**	**Car(1)**	**Car(2)**	**Car(1)**	**Car(2)**	**Car(3)**	**Car(4)**
Monthly car repayments	$200.00	$250.00	$150.00	$500.00	$400.00	$200.00	$250.00	$150.00	$400.00
Colour	Red	Blue	Black	Silver	Green	Red	Black	Silver	Green
Body Type	Sedan	Coupe	SUV	Ute	SUV	4WD	Coupe	Sedan	Coupe
Comfort Rating (1-5)	3	4	5	4	4	3	4	5	4
Performance rating (1-5)	3	4	5	3	4	3	4	5	4
Pollution rating (0-10)	8	6	7	8	7	4	3	4	6
Number of cylinders	4	6	6	6	6	4	6	6	6
Fuel type	Petrol	Hybrid	Petrol	Petrol	Petrol	Petrol	Diesel	Hybrid	Petrol
Number of seats	5	5	4	3	5	5	5	4	5
Odometer reading	40,000	35,000	50,000	20,000	22,000	80,000	85,000	60,000	70,000

Table 6 presents the predicted choice shares for each decision maker described in Table 5 assuming the two models reported in Table 3. To obtain these results, 10,000 randomised Sobol draws (see Hensher et al. 2015) where used to simulate the random parameters, and correlated error terms of the models (including Probit and Tobit models). Reported within the table are the choice probabilities obtained for the three decision makers with regards to selling an existing household vehicle, as well as purchasing a new vehicle. Comparing the results obtained from applying the two models to decision maker 1, the first model predicts that current household vehicles one and two will be sold with probabilities of 0.092 and 0.146 respectively, which change to 0.116 and 0.156 respectively when the second model is applied instead. As such, the first model predicts slightly lower probabilities that both vehicles will be sold relative to the second model. Large differences begin to emerge however when the results of the car purchase model are examined. In particular, whilst both models predict the no choice alternative as being the most likely outcome, the probability that none of the vehicles will be chosen increases significantly when the second model is used compared to when the parameters from the first model are applied.

Table 6: Choice probabilities for models G1 and G2

	G1	G2	G1	G2	G1	G2
	Person #1		**Person #2**		**Person #3**	
Sell existing vehicle fleet						
P_{sell}(vehicle #1)	0.092	0.116	0.275	0.173	-	-
P_{sell} (vehicle #2)	0.146	0.156	-	-	-	-
Purchase new						
$P_{purchase}$(Car1)	0.144	0.066	0.064	0.113	0.168	0.055
$P_{purchase}$ (Car2)	0.113	0.104	0.286	0.130	0.088	0.089
$P_{purchase}$ (Car3)	0.274	0.186	-	-	0.178	0.138
$P_{purchase}$ (Car4)	-	-	-	-	0.070	0.063
$P_{purchase}$ (none)	0.469	0.644	0.650	0.757	0.496	0.655

Further, whilst both models predict that the third of the three vehicles has the highest probability of being selected, the first model assigns the next highest probability to vehicle one being chosen, whilst the second model assigns a higher probability to vehicle two being chosen over vehicle one. Looking at the second decision marketer, the probability that the single existing household vehicle will be sold drops from 0.275 to 0.173 when moving from models G1 to G2. For the same decision maker, as with the first, the probability that no vehicle will be chosen is greater for the second model, than for the first, however for model based on treatment group G2, there appears to be a greater degree of possible trading between the two vehicles that make up the market, with the probabilities for the two alternatives being relative close to each other. In contrast, application of the first model assigns a significantly higher probability that the second vehicle will be chosen relative to the first. For the third example decision maker, there exists a large discrepancy between the models in terms of the predicted probability that the first vehicle will be chosen out of those available. Application of the first model predicts that this vehicle has the second highest probability of being chosen, ignoring the no choice alternative, whilst use of the parameters from the second model assigns the lowest probability to this vehicle being selected. Whilst the other differences in the choice probabilities for the remaining three vehicles are observed to occur, these discrepancies are relatively minor compared to that of the first vehicle. Similar to the other two decision makers, there exists a substantial increase in the probability of the third decision maker not choosing any of the available vehicles.

To demonstrate the relationship between the vehicle car repayment budget item and the other outside goods, we plot indifference several curves for the three decision makers described in Table 5, based on the model obtained for treatment group G2. Plotted in Figure 7, are the indifference curves for expenditure on car repayments against expenditure for savings, rent/mortgage and entertainment. We do this for three different amounts of total utility, $U(\boldsymbol{x}_{nt})$, these being total utility equal to 1, 2.5 and 5. The slopes of the indifference curves represent the marginal rates of substitution between the budget items shown on the axis of each subplot. The constant slops for each curve suggests that over the range of expenditure patterns explored, each plotted budget item represents a perfect substitute for expenditure on car repayments. To understand why such an outcome arises, we note that the model predicts very low values for each ψ_c alongside relatively large estimates for the γ_c parameters. Further, as can be seen here, the slopes of the curves differ by decision maker as a result of the utility

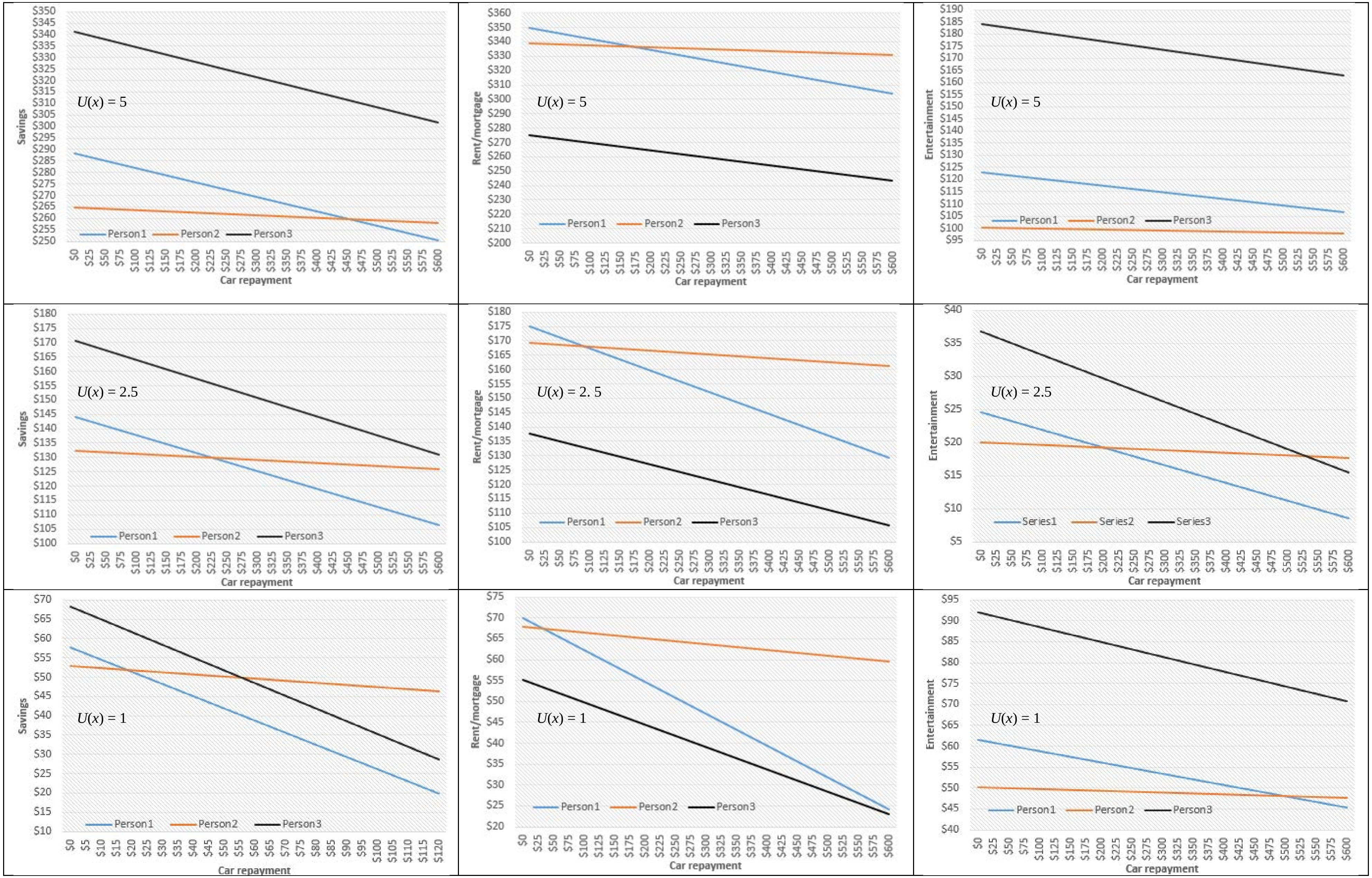


Figure 7: Example indifference curves for different values of $U(x)$

for each expenditure item being a function of socio-demographic characteristics, both in terms of the ψ_c and γ_c parameters, with the resulting slope also depending on the value of $U(\boldsymbol{x}_{nt})$, which would in practice depend on an endogenous decision maker specific budget constraint.

4.0 DISCUSION AND CONCLUSIONS

In this paper, we have presented the results of two empirical case studies in which respondents were exposed to a SC experiment in which they were asked to not only make a series of interrelated choices, but also make decisions as to how they would reallocate their existing household budget in light of those choices. The context of both experiments is vehicle choice. In the first case study, respondents first completed a SC task, which was subsequently repeated but with the additional requirement of having to indicate how they would adjust their household budget given their choice. The survey allowed respondents undertaking the second task to change their choice from their original decision when confronted with the budgetary consequences of their choice. If the 'none' alternative was chosen, no budget reallocation was required. Our expectation was that respondents would find the additional budget task too difficult to answer and hence avoid having to do the budget reallocation by choosing the 'none' option in the SC task. Of the 912 respondents, 315 choose the 'none' option in both tasks, whilst 155 respondents who had previously chosen one of the non-no choice alternatives switched their choice to the no choice alternative, and hence avoided having to answer how they would readjust their household budget. Whilst it is not possible to disentangle whether any of the 155 respondents who changed their choice towards the no choice did so as to avoid having to complete the budget reallocation task or whether they did so once they were confronted with the budgetary reality of their decision, it is likely that the later reason was the cause of the switch for at least some of these respondents. Encouragingly, 207 respondents who previously had previously chosen the no choice alternative switched their choice away from the no choice option, and hence had to respond to the budget reallocation task. As such, these respondents elected to undertake the more onerous budget reallocation task which they could have avoided by sticking with their original no choice selection. It is also worth noting that an additional 228 respondents completed the budget reallocation task by either retaining their previously selected non-no choice option, or switching to an alternative non-no choice option. Of critical importance however, is the fact that 376 or 41.23 percent of respondents changed their choice from their initial selection when confronted with having to undertake the household budget reallocation task.

Using the same SC context as in the first study, the second case study divided the sample into two treatment groups, the first of which was asked to complete a series of traditional SC type questions, whilst the second treatment group were required to complete a similar series of SC questions alongside a household budget reallocation task. As such, the second case study represents a between subject replication of the first study. Random assignment resulted in both samples being statistically equivalent based on all socio-demographic criteria save one, gender. For the second treatment group, we implement a series of models describing the choice of vehicle, including models related to supplementary choices related to the sale of existing vehicles and the use of savings, all of which are linked to a MCDEV model used model the budget reallocation questions, which in turn relates back to the vehicle choice via the no choice option.

Significant differences in the results of the models estimated on the two treatment groups are found, with different patterns of preference located for the various attributes of the experiment. Of particular interest, the price sensitivity of the second treatment group was found to be significantly lower than that of the first, whilst the second treatment group was also found to have a higher probability of choosing none of the alternatives on offer. The higher probability for the no choice in the second group was the result of a sign reversal associated with the no choice ASC, as well as the inclusion of the utilities associated with the budget categories of entertainment and rent/mortgage as derived from the MCDEV model. This later finding suggest that respondents with a higher utility for expending income on entertainment and rent/mortgage, are less likely purchase any of the vehicles offered in the SC tasks.

Without RP data, it is not possible to definitively conclude that the inclusion of the budget reallocation task results in a more incentive compatible survey response, however, conceptually we argue that this is more likely to be the case. This finding is in line with the suggestion by both Wardman (2001) and Brownstone and Small (2005) that one of the major sources of discrepancy between the marginal willingness to pay (mWTP) between stated preference (SP, of which SC is a particular type) and RP data is due to respondents incorrectly judging their true budget constraint in SP survey tasks. For completeness, we report the median mWTP values for the vehicle attributes in Table 7. The mWTP reported in the table are calculated using 10,000 simulated random Sobol draws and are based on the unconditional estimates reported in Table 3. We do not report confidence intervals for the mWTP distributions as these are very large given the amount of preference heterogeneity present within the data, making them useless for statistical significance tests (see Bliemer and Rose 2013). Without confidence intervals, we refrain from making any definitive statement regarding the mWTP estimates obtained for the two treatment groups, noting only that at least visually there appear to be significant discrepancies between the values obtained from the two groups, with sign reversals observed for the mWTP for several of the attributes. Independent of the mWTP results, we argue that the inclusion of the budget reallocation task enforces the budget constraint upon the SC decision, given that respondents are unable to proceed in the survey until they balance the budget.

Table 7: Median mWTP estimates for samples G1 and G2

	G1	G2
Vehicle colour: Blue	$4.02	$0.00
Vehicle colour: Green	$0.00	$47.98
Vehicle colour: Red	$0.00	$101.98*
Vehicle colour: Silver	$0.00	$106.26*
Vehicle type: Coupe	-$1.46	$54.53
Vehicle type: Hatchback	$0.00	$92.19*
Vehicle type: Sedan	-$54.23*	$0.00
Vehicle type: Station wagon	$0.00	$288.27*
Vehicle type: SUV	-$55.89*	$0.00
Vehicle type: Ute	$53.17*	-$10.80
Comfort rating	-$8.37*	$1.41
Diesel fuel	$20.08	$25.81
Num. of Cylinders	$0.48	-$2.70
Number of seats	-$9.85*	-$27.50*
Odometer	$2.54*	$29.80*
Performance rating	-$12.81*	-$6.48
Pollution rating	$0.00	-$9.53
W(Entertainment)	-	$1.54
W(Miscellaneous)	-	$3.93
W(Rent/mortgage)	-	$6.89*

* Mean parameter of the random parameter distribution was statistically significant (see Table 3)

With regards to the finding that respondents who were asked to undertake the budget reallocation task being less price sensitive than those who did not, we note that such a finding may at first appear somewhat counterintuitive. This is because one would expect respondents completing the budget reallocation task to be more focused on the cost implications of their decision and hence be more sensitive towards price. The fact that the opposite effect was found requires some explanation. We therefore posit three possible causes as way of explanation for why we observe the opposite effect here.

Firstly, it is necessary to consider the entirety of the response mechanism respondents were exposed to, not just the budget reallocation task. Rather than simply make a choice in the SC task, respondents were also able to offset any cost for purchasing a vehicle via the allocation of existing savings, and/or the use of funds obtained from selling an existing vehicle. Whilst respondents allocated to treatment group G2 are less likely to sell an existing vehicle in order to offset the cost of purchasing a new vehicle relative to those assigned to treatment group G1, respondents in the second treatment group appear to have engaged with the savings aspect of the response far more than those assigned to the first group. Thus, whilst respondents within the second group have a higher propensity to not select any vehicle in the SC task when compared to those allocated to treatment group G1, when a purchase decision is made, they appear to be more inclined to increase the number of vehicles held within the household and do so using existing savings. Thus, whilst the inclusion of a budget reallocation task within a SC framework may enforce both a hard (i.e., one cannot expend more than ones budget, at least in the long run) and soft (e.g., psychological thresholds) constraint on consumption affecting the purchase/no purchase decision, other related decisions that affect cost may be equally important in affecting how sensitivity individuals are towards cost. Whilst such a finding, if generalised beyond the current study, is less likely to affect certain consumption goods, particularly low cost goods such as day to day travel, for other goods, our study raises the possibility that the hypothecation of alternative sources of funds towards specific purchases may result in different degrees of price sensitivity. If such an effect is found to be the case, this suggests that the study of demand for many goods and services cannot be accomplished effectively without consideration as to how consumers intend to fund such purchases. We hypothesis that such an effect is more likely to occur for the purchase of a good that replaces an existing similar good, however such an effect may extend to other purchase contexts. In the age of e-commerce and online auctions, our findings suggest that it is imperative to first identify whether such an effect is indeed naturally occurring, and if so, for what types of goods/services such a process is most likely to affect. Finally if confirmed, we also note that such an effect may open up additional indirect mechanisms for policy makers to influence behaviour (i.e., one can explore alternative funding mechanisms as opposed to being limited to adjusting the attributes or characteristics for the goods within a market).

Secondly, as alluded to above, the budget reallocation task not only enforce an upper hard constraint on consumption, but as shown in the first case study, may also reveal a lower psychological soft constraint in the form of specific threshold expenditure amounts for different budget categories. As noted, the budget allocation task in the current empirical setting appears to influence the purchase/no purchase decision, meaning that the vehicle price for those who do make a purchase decision must fall not only below the hard budget constraint, but also the soft psychological constraint. From an economics perspective, this suggests a kinked demand curve for individuals, with a downward sloping demand curve that becomes perfectly inelastic once the soft budget constraint is exceeded. Whilst we are unable to state with certainty, we hypothesis that within the SC task, the budget reallocation task may have resulted in a more elastic demand curve up until the point of inflection relative to those who did not undertake the task, as the task itself may have acted either as a reminder of the soft constraint imposed by the individual, or allowed respondents to understand that they have possess such a constraint which otherwise may have previously been unknown to them. We do not however wish to generalise such an effect beyond the current consumption good examined without further research however. This is because, if such an effect does exist, it may operate differently for different types of consumption goods. Further, research is required to understand whether respondents undertaking traditional SC questions without having to perform a budget reallocation task are aware of any budget threshold, and if so, whether the inclusion of the budget reallocation task psychologically can shift the threshold. If no such threshold exists within a traditional SC framework, then research is required to determine firstly why not, and secondly whether the threshold effect derived from the budget reallocation task is indeed a real world phenomenon or simply some artefact of the survey itself.

The final possible cause for the observed reduction in price sensitivity arises from a possible mis-specification of the random parameter distribution used to model the marginal disutility associated with the cost attribute for the second treatment group. Consistent with the literature, we have imposed a lognormal distribution for price so as to enforce diminishing marginal utility with respect to price, however for treatment group G2, we observe not only a decrease in the mean and median price sensitivity, but also a significant decrease in the variance term representing preference heterogeneity. We hypothesis that the observed reduction in preference heterogeneity may arise due to a number of factors. Firstly, previously observed preference heterogeneity may have arisen due to purchase uncertainty in the traditional SC task, which was mitigated somewhat by the budget reallocation task. As such, the budget reallocation task may have resulted in individual respondents who previously displayed greater or lesser preference sensitives to opt out of the market, leaving decisions makers with a more homogenous preference structure. Secondly, the budget reallocation task itself may prevent overt displays of extreme price sensitivity that can otherwise occur without such constraints in place. Such an effect is likely to arise as a result of hard constraints being imposed on all respondents in the experiment, which otherwise may have psychologically been ignored by subsets of respondents when no budget constraint was enforced on the decision process. If true, we would argue that the price sensitivity derived for the SC only segment may be an over inflated artefact of the experiment itself, whereas the values obtained from the second treatment group are more likely to better reflect reality, assuming of course the decision makers are confronted with markets similar to that described within the experiment. Independent of the precise cause, the tail of the lognormal distribution reflects extreme price sensitivity that either cannot exist, or may not exist when the budget reallocation task is incorporated into the survey.

Our findings also support the possibility that SC experiments may violate the economic concept of preference separability, even in the presence of a no choice alternative. We found that utility associated with expenditure on the outside goods categories of entertainment, miscellaneous spending and rent/mortgage influence the choice of vehicle in our SC experiment, at least insofar as they influence the choice as to whether or not a vehicle will be chosen or not. Reported in Table 7 are the MRS between the utilities for expending income on entertainment, miscellaneous spending and rent/mortgage and the cost of purchasing a new vehicle based on the SC results, the mere existence of which suggest that respondents are trading between these budget categories and vehicle choice. We argue however that care need be taken in generalising these results. For the present study, we deliberately chose a decision context that involves a significant cost to decision makers. That is, given the price of automobiles, the purchase of a vehicle is likely to have a significant impact upon a household’s budget. It is less clear whether this finding will translate to goods or services that are lower cost, and hence have less impact on a household’s budget, or even habitual goods. Examination of both types of goods represents an interesting research opportunity, particularly with regards to low cost, but frequently purchased goods, such as toll road patronage. For such goods, an open question is whether decision makers consider each point of consumption as a separate decision, such that each purchase represents a relatively small impact upon ones budget, or make decisions aggregating across consumption points, such that the total cost of multiple purchases is what drives choice. For habitual choice, one interesting research question is whether it is possible to induce changes to what ordinarily would be considered to be exogenous outside goods, so as to break the habitual choice pattern rather than examine simply the role endogenous attributes typically play in such choices.

Further research is also required to determine the cognitive limitations of respondents in answering questions similar to those used here. As stated previously, it is not possible to untangle whether respondents are selecting the no choice alternative to avoid having to complete the budget reallocation task. With that said however, we take at least partial comfort with some of our findings from the first study, where a larger number of respondents elected to undertake the budget reallocation task when they need not have, compared to the number of respondents who for unknown reasons opted out of performing the task. Unfortunately, the possibility that respondents may act in this manner is likely to result in models overstating the probability of the no-choice being selected, as well as impact upon the mWTP results obtained from such models, particularly if the no choice alternative is treated as a cost free status quo alternative with parameters that are specified as being generic to the other hypothetical non status quo alternatives. It is not clear how such research might be undertaken, however qualitative research of some nature is likely to be required.

Our research approach also opens up one additional tantalising line of research enquiry. For the current study, we have used the SC experiment to force respondents to make adjustments to their household budget choice. Reversing this, our approach offers researchers the ability to adjust hypothetically a respondent’s budget, and then observe how this will impact on the decisions made in a SC experiment. For example, our approach will allow analysts to hypothetically adjust say the monthly rent/mortgage payments of respondents, simulating a rent or interest rate rise, and observe how this will affect the choices respondents make in a SC setting, such as a mode choice experiment. A such, our proposed method will allow analysts to explore how exogenous macroeconomic events affect important choices as well as commonly used economic variables, such as the value of time.

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