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Electric vehicles adoption: Environmental enthusiast bias in discrete choice models

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ABSTRACT

A Stated Choice (SC) survey, employing a Best-Worst choice design, was administered to 440 households in Perth, Australia as part of a major investigation into consumer preferences and attitudes towards electric vehicles. It was noted that 48 (10.9%) respondents chose EV as their best/most preferred option across all six choice replications. We hypothesise that for most of these respondents their choices reflected their desire to present themselves in a favourable light, with social desirability biasness manifested in non-trading behaviour. There were also 24 (5.5%) respondents who chose EV as their worst/least preferred option. We hypothesise that for these respondents lack of interest or confidence in the new technology and inertia may have driven their decisions. The paper offers demographic and psychographic profiles of non-traders facilitated by additional items being included in the experiment. While there was little difference between the demographic profiles, the attitudinal scores of the non-traders were significantly higher than for traders, which may indicate social desirability. Non-traders (Best) scored significantly higher on environmental concerns and subjective norms and were more likely to rate their intention to purchase and use an EV higher. Conversely, non-traders (Worst) had the lowest environmental concerns and subjective norms. From a choice modelling perspective, keeping non-traders in the estimation biases the taste parameters and therefore the willingness-to-pay (WTP) measures. However, when incorporating the worst alternatives into the choice models, the 'social desirability' non-traders do appear to be making decisions based on the attributes, which is consistent with the rest of the sample.

1. Introduction

The recent revival of electric vehicle (EV) technology is in its early days and in markets like Australia the number of EV's on the road is very small. With limited real market data available, stated choice (SC) experiments have emerged as a popular tool to study the factors influencing the uptake of EVs. Typically, this involves participants being presented with a set of vehicle and fuel alternatives (including the EV) and choosing their preferred alternative by trading-off key attributes such as purchase price, running costs, environmental performance, safety, range, and refuelling/recharging considerations (Kurani et al., 1996; Dagsvik et al., 2002; Hess et al., 2006; Lieven et al., 2011; Ziegler, 2012; Bühler et al., 2014). This information can in

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turn be used to identify the relative importance of each attribute both across the sample and by socio-demographics and market segment.

While SC experiments can yield rich information on consumer preferences, they are prone to a number of issues impacting their validity. First, because they are based on hypothetical choices, there may be a distinct gap between stated intention and actual purchase behaviour, what has been coined, *hypothetical bias* (Hensher, 2010). Second, there is a continuing tension between capturing the complexities of choice decisions without over-burdening participants (Caussade et al., 2005). Third, as hybrid choice models – models that incorporate latent variables and constructs into the choice model – become more the norm rather than the exception, SC experiments are also surveys of attitudes and perceptions. As such, they are subject to a number of response biases – including demand characteristics and social desirability (Nichols and Maner, 2008; Lusk and Norwood, 2011). Fourth, SC requires participants to *trade-off* choices based on varying the levels of attributes. If this non-trading is significant, it is: (i) important to try to assess whether this is genuine or non-genuine, (ii) if genuine, what the reasons, and (iii) assess the impact of this non-trading on the preference parameters and conclusions drawn from the choice modelling results.

In the case of EVs, which may present a highly polarising choice, levels of non-trading may be non-trivial. This could reflect the desire of respondents to present themselves as environmentally friendly to others. In this case, responses are subject to so-called 'social desirability' bias. Another possibility is that respondents are attempting to understand the purpose of the experiment and subconsciously change their behaviour (Orne, 1962). One way in which respondents alter their behaviour is to comply with their understanding of the researcher's aims. This is known as the 'good subject' effect (Nichols and Maner, 2008). However, often this issue is overlooked and/or not accounted for in the subsequent choice modelling.

With this in mind, the current paper presents analyses of non-trading behaviour observed during a SC experiment conducted as part of the Western Australian Electric Vehicle Trial (WAEVT), with a sample of 463 households. The experiment employed a Best-Worst (B-W) design. B-W is an adaptation of SC in which participants selected their most preferred (best) and least preferred (worst) option among four vehicle types, namely EV, Plug-in Hybrid, Diesel, and Petrol. This was repeated over six choice tasks. Initial analysis of the results suggested significant levels of non-trading with 48 (10.9%) of respondents always choosing the EV as their best alternative, and 24 (5.5%) always choosing EV as their worst alternative. The study presented here did not anticipate the extent of non-trading responses and as such no additional attempt was made to identify the respondents on a social desirability scale (e.g., Crowne and Marlowe, 1960). However, a number of attitudinal measurements based on the theory of planned behaviour (Azjen, 1991) and the technology acceptance model (Davis, 1989) augmented the experiment. The paper explores the responses to the attitudinal items to uncover possible reasons for the non-trading behaviour in the stated choices, before assessing the impact of the inclusion of non-traders in choice models on taste parameters and therefore willingness-to-pay (WTP).

The paper is organised as follows. The literature review briefly considers the key factors behind EV uptake before focusing on how SC experiments have been used and refined to elicit preferences with specific consideration of non-trading and bias. Following this, is a description of the conceptual approach and survey instrument before details of the fieldwork are provided. We then present a demographic and psychographic profile of non-traders, facilitated by the additional attitudinal variables to uncover plausible reasons for the non-trading. The paper investigates the impacts of this non-trading on model parameter estimates and whether the respondent's indicated Worst choice provides information on their preferences, even if they are not trading when responding to their Best alternative. Finally, conclusions are drawn as to the importance, reasons for, and impacts of non-trading on inferences drawn with regards to EV preferences.

2. Literature review

The review of the literature is organised as follows. First, we consider recent evidence on EV uptake and the key factors behind this uptake (Section 2.1). Section 2.2 outlines the rationale for and evidence obtained from SC approaches in the context of EVs (2.2.2), before specific consideration is given to the Best-Worst (B-W) approach. B-W offers certain advantages over traditional SC experiments, described in Section 2.2.3. Finally, we consider the reasons for and problems caused by non-trading behaviour in choice experiments with specific consideration of factors that could be causes of (genuine) non-trading in EV scenarios (2.3).

2.1. Electric vehicle uptake

The concept of an electric vehicle is by no means new and in fact pre-dates internal combustion engine (ICE) vehicle technology. However, following decades of relative obscurity, with only niche applications employing EV technology (e.g., forklifts, golf carts), there has been a slow but assured resurgence recently, as many of the technological/practical barriers have been lowered, particularly in parts of Europe and to a lesser extent the U.S. and Japan. Norway and the Netherlands have seen their EV market share rise to over 5% of new car sales since 2013,[1] a reflection of assertive government policy responses to growing fuel security and environmental concerns designed to make EVs more appealing both financially and pragmatically to consumers (Figenbaum et al., 2014). By contrast, Australia, where the current study was undertaken, is a relative laggard,

[1] http://www.abb-conversations.com/2014/03/electric-vehicle-market-share-in-19-countries/. Accessed 25/11/15.

with an EV market share of 0.04% as of 2014 (ClimateWorks, 2016). Price remains a major barrier, with few meaningful incentives around the initial purchase of the vehicle or on-going costs (AECOM, 2009). However, recently purchase prices have begun to fall, which will likely accentuate the importance of other known barriers to wider EV adoption, primarily around 'range-fear' and recharging requirements (Lin and Greene, 2011).

2.2. Methodological approaches to investigate EV markets

As a relative newcomer to this space, Australia has the benefit of learning from the many overseas investigations of factors impacting EV adoption. The earliest investigations of the acceptance of 'new-age' EVs, came out of market analysis conducted in the late 1990s in California (Kurani et al., 1996; Golob and Gould, 1998). Kurani et al. (1996) were among the first researchers to incorporate attitudinal data in their design. Their findings indicated that environmental concerns may not have had much influence on the market initially, though they are clearly a motivating feature for choosing EVs given zero tailpipe emissions. Since this time, there have been several studies exploring EV adoption from a marketing perspective (Ewing and Sarigollu, 2000; Egbue and Long, 2012; Peters and Dütschke, 2014; Bailey et al., 2015). These studies have identified price, increase in range of the vehicle, fast charging and improved charging infrastructure, along with awareness about EV characteristics, environmental benefits, and EV readiness as the main EV market influences.

2.2.1. Marketing studies

EV infrastructure is what really makes EV a contemporary new technology. This makes it pertinent to explore acceptability of EV in a similar way to "*new technology*" adoption. EV adoption studies explore attitudinal data by applying consumer adoption models such as: theory of planned behaviour (TPB) by Azjen (1991); or diffusion of innovation theory (Rogers, 2003). Schuitema et al. (2013) and Egbue and Long (2012) applied TPB, and Ozaki (2011) applied diffusion of innovation theory for EV/hybrid vehicles adoption.

2.2.2. Stated choice experiments and EVs

Given the limited opportunities to study EV adoption in real markets, most of these investigations have used SC approaches. While most studies have explored the core attributes of EV technology, only a subset has incorporated attitudinal data. Following Kurani et al. (1996) and Ewing and Sarigollu (2000), Bolduc et al. (2008) estimated hybrid choice models incorporating perceptions and attitudes that referred to environmental concerns and appreciation of new car features. In the SC experiment, they did not consider range as an attribute, including only the capital and operating costs, fuel availability, and emissions. Ziegler (2012) explored consumer preferences through SC experiments, with taste persistence included in the choice set, but without attitudinal data. An advanced DCM – multinomial probit model (MPM) – with an inclusion of taste persistence across choice sets, particularly the environmentally friendly aspects, was estimated; Ziegler (2012) found that younger potential car buyers show higher preference for natural gas vehicles as compared to Petrol for their journey to work; they usually purchase environmentally friendly products and own a second vehicle, which runs on biofuel. Hidrue et al. (2011) conducted an SC experiment using latent class modelling (LCM) to explore EV acceptance. They found that savings in the fuel costs tended to lead to the purchase of EVs; range anxiety, charging time, and high purchase price remained in general consumers' main concerns, and a reduction in the cost of the EV battery appreciably increases EV acceptance. However Hidrue (2010) did not assess the excitement for new technology construct, nor the influence of social norms that might affect EV purchase decisions. In their recent study, Kim et al. (2014) used the maximum simulated likelihood to estimate their hybrid MNL, instead of using a latent class or a mixed logit model. Kim et al. (2014) incorporated attitudinal data into the estimation of hybrid choice model and found that environmental and innovation aspects of EV have positive impact on intention to purchase EVs, while battery, economic and technological aspects of EV have a negative impact on intention to purchase an EV.

More recently, where it has been possible to study EV adoption in real markets, there is evidence that attitudes to EVs change, both for better and for worse. Bühler et al. (2014) looked at EV drivers' experiences in Germany and found that after driving EVs for three months drivers' reported lower running costs, ability to charge at home, and low noise as the advantages of EVs. In Norway, EV adopters have reported on the positive side, lower operating costs, quieter vehicles, and (importantly) meeting their needs most of the time, while on the negative citing negative performance in the winter (Figenbaum et al., 2014). In Denmark, Jensen et al. (2014) found that experience with EV reduced user preferences largely because it exacerbated concerns over limited driving range and charging issues.

2.2.3. Best-worst choice experiments

Rooted in Random Utility Theory, Best-Worst (B-W) choice analysis was developed by Louviere and Woodworth (1990). B-W analysis is an adaption of SC methods in which participants select their best/most preferred option and their worst/least preferred option from each choice set. As described in its first application the best-worst (B-W) scaling allows for richer information (Finn and Louviere, 1992). For a set of three alternatives, B-W provides a complete ranking, whereas with four alternatives, a partial ranking can be achieved. Despite its continuous use, the formal statistical and measurement properties of B-W were demonstrated only in 2005 (Marley and Louviere, 2005). As shown by several recent studies in marketing (Cohen, 2009; Auger et al., 2007) and health economics (Flynn et al., 2007), B-W scaling is considered better than complete ranking, because it is easier for a respondent to select the best and worst choices, and thus it is expected to provide more meaningful data. Collins and Rose (2013) found that scale may vary across individual ranking; considering this observation they analysed a difference in scale across the best or worst options chosen by respondents.

2.3. Non-trading and response bias

Non-trading is when a respondent chooses one alternative as best case in all given choice sets (Hess et al., 2010) and may be more relevant to labelled choice experiments. Hess et al. (2010) identified three different reasons for non-trading by respondents, that are: utility-maximising agents (indicates strong preference for an alternative as compared to other alternatives), heuristics (misunderstanding/boredom), and policy-response bias. For the last two reasons it is best to remove non-trading respondents from analysis, but for utility maximising behaviour, when a respondent holds a strong preference for a particular alternative, the data should be kept in the model. The problem is, invariably, that it is not possible to determine a priori, the real cause for a respondent's non-trading behaviour without a follow-up interview.

Researchers have attempted to use other survey information to indirectly assess the presence of non-trading. Guo and Qiu (2010) made use of computer log files to identify respondents who raced through an stated choice experiment. These respondents were identified with the latent class of non-traders and random selections, and the time required to analyse the experimental designs explained differences for the non-trading behaviour. Although not related to non-trading, Cook et al. (2012) showed that "time to think" (TTT) could explain much of the gap between real and hypothetical WTP in experimental studies. This in turn has substantial policy implications.

Another bias that affects responses in stated choice studies is hypothetical bias (Hensher, 2010; Fifer et al., 2014). Mitigation techniques recently recommended include: the use of a cheap talk script (alerting to the hypothetical nature of the situation that is investigated, and especially relevant when participants have no experience with the decision scenario), and the inclusion of a certainty scale to test for the hypothetical bias effects (Fifer et al., 2014).

2.3.1. Demand effects/characteristics

Demand effects/characteristics refers to situations in which participants have awareness of the study's true purpose or hypotheses and try to act accordingly (Orne, 1962; Nichols and Maner, 2008; McCambridge et al., 2012). The involvement of the participant, taking on a role in the experiment, means, most of the time, a more positive response than expected otherwise. This is known as the 'good-subject' or 'good-participant' (helping rather than ruining the study) and may sometimes overlap with the social desirability bias (the participant answers as she/he perceives it is socially desirable or acceptable). Although less frequently found, participants may also attempt to disprove the hypotheses – the 'negative-participant' role (Leroy, 2011).

In a psychology study examining the effect of having knowledge of a study's hypothesis on the subject behaviour during an experiment, Nichols and Maner (2008) found that participants acted as good subjects. Yet, the extent to which participants conformed with the hypothesis was related to their attitudes towards the experiment and experimenter. More positive attitudes meant more good-subject responses. But negative relations were found between socially desirable responses and reactions to participant demand (p. 161).

In a recent review, McCambridge et al. (2012) pointed out the absence of high quality experimental data in non-laboratory conditions to test demand characteristics. A good-participant response may be a result of conforming/complying with an authority, be a result of self-awareness or reflective of altruism. They continue by stating that: "*Little can be securely known about the effects of demand characteristics on participant behaviours across these studies as a whole. Diverse definitions of what constitutes demand characteristics have been used, ranging from awareness of conduct of research or being watched and their effects on actual behaviour, to reporting artefacts or some combination of both.*" (p. 5)

This indicates that many factors could influence individual differences in the extent to which respondents submit to demand and they are likely to combine, with non-negligible effects in research findings.

2.3.2. Social desirability

Social desirability is the tendency to respond to questions in a socially acceptable direction, thus to report more favourably certain attitudes and behaviours (Bonsall, 2009; Leroy, 2011; Norwood and Lusk, 2011). This mainly occurs for questions that are charged with personally or socially sensitive content (Norwood and Lusk, 2011). Where positive features, behaviours, and attitudes (voting, physical activity, charitable giving) are anticipated, positive answers are amplified (Holbrook and Krosnick, 2010; Brenner and DeLamater, 2014; Lee and Sargeant, 2011); conversely, responses for negative behaviours or stigmatised attitudes (substance abuse, illegal behaviour, violence, or racism) are diminished or hidden (Krumpal, 2013). Related to the tendency of misrepresenting the true attitudes or behaviour is the fact that only a subset of the respondents recruited for studies tend to participate. This exclusion from the target population or under-representation of certain segments of the population, may exacerbate the effects of systematic deviation from the true population parameter.

Social desirability can be intentional or unconscious/unintentional. Two primary factors affect social desirability: general predisposition and/or the aspect being examined, with some subjects more likely to elicit socially desirable behaviour. When anticipated, social scientists apply a number of methods to minimise its influence: psychometric scales, controlled experiments (Norwood and Lusk, 2011), bogus pipeline (Krumpal, 2013), careful choice of the survey method and craft of the instrument. Many studies found that this desirability effect is exacerbated by the interviewer's presence. But even offering anonymity, such as in the self-completed questionnaires, does not resolve the issue. Providing an email address for a prize (or even sufficient socio-demographic information about the respondent) may amplify socially desirable answers and distort the findings.

The magnitude of its impact is yet to be determined. Social desirability is highly contextual and in the absence of experiments accounting for this potential bias and/or post-survey information on the respondents, few metrics are available for assessment (e.g., social desirability scale, Weiner and Craighead, 2010). Yet, Norwood and Lusk (2011) warn that stronger correlation between the scale of desirability (SDB) and behaviour *"is not a measure of the overall level of SDB, when the cost of exhibiting SDB differs across people or treatments*" (p. 534) and they propose the use of inferred valuations as an alternative to scales and non-hypothetical experiments. Questioning of the effect of SDB scale is not new. Armitage and Conner (1999) found no moderating effect of social desirability on relationships between TPB components, thus they supported the use of TPB predicting intentions and behaviour; in another study, perceived behaviour control independently predicted intentions and behaviour (Armitage and Conner, 2001), suggesting that subjective norms are a weak predictor in TPB.

3. Methods

3.1. Conceptual model

The conceptual model for this study is presented in Fig. 1. This brings together the explanatory variables, such as purchase price and range, with the latent variables (detailed in the next paragraph), and the stated purchase decision. Unlike the Technology Acceptance Model (TAM), where behaviour is defined indirectly by intentions (Davis, 1989), here individual behaviour is defined through choice, reflective of the attitudes. Attitudinal data are defined through latent constructs and then incorporated into the utility function of the choice model. In this way, a hybrid discrete choice model is formed to use as explanatory variables in the utility specification, both attributes of the alternatives and characteristics of individuals, as well as the attitudinal data.

The attitudinal dimensions chosen as relevant for the decision to purchase an EV are: (i) *Environmental concerns (EC)*; (ii) *Excitement for new technologies (ENT)*; (iii) *Perceived usefulness (PU)*; (iv) *Subjective norms (SN)*. Environmental concerns have already been used by a large number of studies that explore EV adoption behaviour (Ewing and Sarigollu, 2000; Dagsvik et al., 2002; Hidrue et al., 2011; Bolduc et al., 2008). 'Subjective norms' as taken from the TPB literature measure the social influence that can effect individual behaviour. 'Excitement for new technologies' and 'Perceived usefulness' both relate to technology adoption scales and are derived from the diffusion of innovation theory, product involvement, and technology adoption scales (Rogers, 2003; Zaichkowsky, 1985; Yang, 2012).

3.2. Survey instrument

The survey instrument comprised a questionnaire designed to capture attitudinal information, vehicle choice decisions, and socio-demographic characteristics. Participants were able to choose to complete either a paper-and-pencil or web-based version of the questionnaire (www.surveymonkey.com), which emphasised on the first page that a number of hypothetical scenarios would be presented for comparison. A brochure also accompanied the survey describing in a comprehensive manner the EV features, infrastructure requirements, and market situation. This information and the note on hypothetical scenarios was a way to alleviate the bias (similar to what Fifer et al., 2014 have recommended). The *Attitudinal* component of the questionnaire included 17 items measuring the four attitudinal dimensions presented in Fig. 1 (Latent factor scores). Questions were adapted from a number of previous scales:

- Environmental concerns (EC) – Ewing and Sarigollu (2000), Dagsvik et al. (2002), Heffner et al. (2007), Hidrue et al. (2011), Ozaki (2011);
- Excitement for new technologies (ENT) – Parasuraman (2000), Meuter et al. (2003);
- Perceived Usefulness (PU) – Ewing and Sarigollu (2000), Meuter et al. (2003), Ratchford and Barnhart (2012);
- Subjective norms (SN) – Venkatesh and Davis (2000), Ozaki (2011), Yang (2012).

Additional changes were made following two focus groups and a pilot survey, to better reflect the local context and very limited adoption of EVs in Australia. Statements were measured on a Likert scale 1–5, with 1 used for 'Strongly disagree' and 5 'Strongly agree'. Confirmatory factor analysis (CFA) was undertaken to calculate the latent factor scores for the four attitudinal constructs. Appendix A.2 presents the items used to reflect the four latent constructs, along with the CFA results.

The *Vehicle Choice* component of the questionnaire was designed to explore the EV purchase decisions using a SC design. Twelve experiments were generated with a block of six experiments randomly assigned to each respondent. As scenario randomisation was not possible for the layouts of this survey, two separate set of experiments were generated and each respondent was presented with six experiments. Four vehicle alternatives: EV, Petrol, Plug-in Hybrid, and Diesel were given in each experiment. Attributes identified against each alternative, along with their levels, are given in Appendix A.1. The

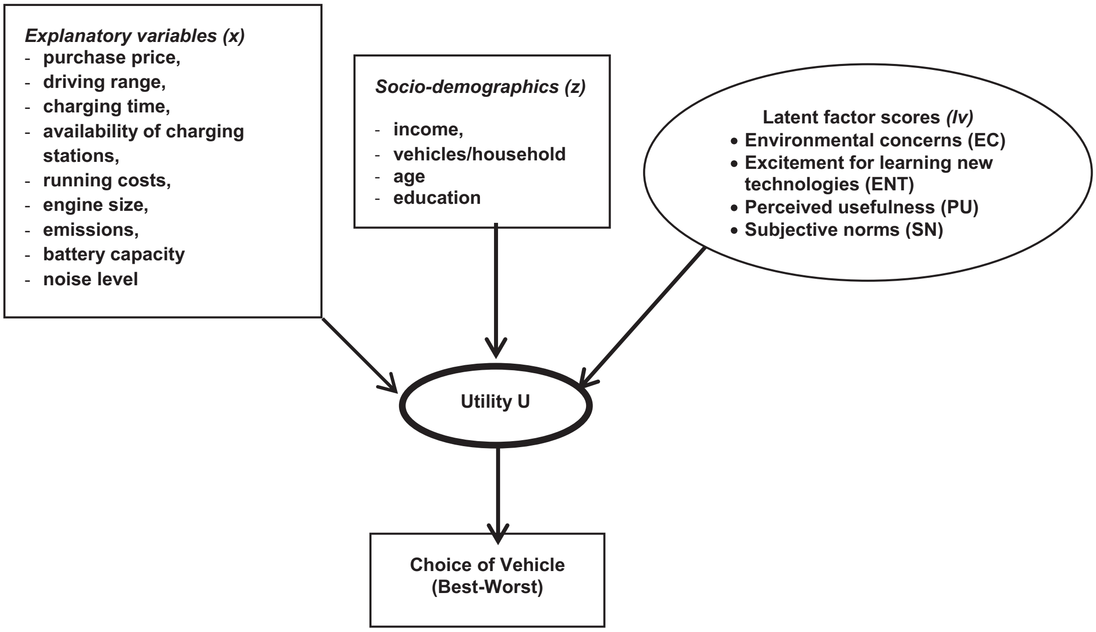

Fig. 1. Conceptual model.

experiments were designed using a GA optimisation to minimise the determinant of the asymptotic matrix of variances-covariances (AVC) for an MNL model and using priors from literature and a pilot study with 22 respondents.

In order to overcome some of the limitations of traditional discrete choice experiments (inefficient way to elicit preference information, cognitive burden for many treatments, confound between attribute weight and level scale – Flynn and Marley, 2014), we opted for Best-Worst tasks. Specifically, we used what is referred to as type 3 Best-Worst, which represents the multi-profile case, where a combination of alternatives with their attributes is shown to the respondents (Flynn and Marley, 2014). In B-W, the respondents are required to indicate the combination of attribute levels that exhibits the highest utility and the lowest utility, assuming in fact that individuals choose that pair of options in each set that differ the most on an underlying latent dimension. This increases the efficiency of estimation and is expected to provide additional information. In this case, participants had to select their best/preferred vehicle and worst/least preferred vehicle from each of the six experimental scenarios.

3.3. Identifying non-traders

Non-traders were identified as those who always selected the EV as their Best option and conversely those who always selected the EV as their worst option across the six choice tasks. In this study, traders and non-traders were compared on socio-demographic characteristics and attitudes. As it was not possible to determine the real cause for the respondent's behaviour, in order to avoid errors in the valuation of attributes, discrete choice analysis was also carried out both with and without non-trading observations.

4. Empirical inquiry

4.1. Fieldwork

Fieldwork was conducted in Perth, Australia, as part of the Western Australian Electric Vehicle Trial (WAEVT). Following direct contacts and an invitation to participate in this study, respondents were given a flyer providing a description of EVs and presenting the Australian market situation. In total, the questionnaire was successfully administered to 463 households of which, 352 (76%) completed the survey by mail with 111 (24%) using the web-based version. After data cleaning, a total of 440 complete responses were used for analysis (7% response rate). Table 1 provides the descriptive statistics for the whole sample in the second last column. Overall, the sample included more male (60%) and highly educated respondents (74.7%). In terms of the attitudinal information, the highest latent score values were recorded for the 'Perceived usefulness of technology' (3.71), followed by 'Excitement for new technologies' (3.55), whereas 'Subjective norms' (2.73) and 'Environmental concerns' (2.66) lagged behind by about one point.

Table 1
Sample profiles: EV non-traders best, EV non-traders worst, and traders.

Variable	Statistic	Traders	EV non-traders (best)	EV non-traders (worst)	Total	ANOVA P-value
AGE (years)	Av.	50.47	46.85	52.50	50.07	0.136
	Stdev.	14.04	14.21	9.83	14.01	
Household income ($000s)[*]	Av.	113.51	112.13	137.38	113.83	0.070
	Stdev.	65.71	65.39	72.42	65.57	
Gender (males)	%	52.08	60.46	67.1	60.05	0.256
Education (post-secondary)	%	74.27	81.25	66.67	74.70	0.133
Number jobs	Av.	1.01	0.90	0.88	0.98	0.515
	Stdev.	0.91	0.66	0.45	0.84	
Buy new car	%	54.17	55.04	71.36	56.94	0.497
Amount willingness to spend for next car (WTS) ($000s)[***]	Av.	*27.14*	30.50	**39.17**	30.80	0.005
	Stdev.	9.18	14.11	18.17	14.74	
Likelihood to buy EV[***]	Av.	2.70	**3.77**	*1.50*	2.76	0.000
	Stdev.	1.28	1.06	0.88	1.31	
When changing car	Av.	3.36	3.39	3.37	3.37	0.958
	Stdev.	1.42	1.66	1.93	1.65	
Without ICE[***]	Av.	2.87	**3.54**	*1.58*	2.85	0.000
	Stdev.	1.56	1.25	1.06	1.53	
Frequency using EV[***]	Av.	3.55	**4.15**	*2.5*	3.58	0.000
	Stdev.	1.2	1.85	1.38	1.21	
Environmental concerns (EC)[***]	Av.	2.65	**2.85**	*2.21*	2.66	0.008
	Stdev.	0.49	0.48	0.71	0.54	
Social norms (SN)[**]	Av.	2.72	**3.40**	*2.35*	2.73	0.013
	Stdev.	1.22	1.52	1.42	1.28	
Excitement for new technologies (ENT)	Av.	3.54	3.75	3.20	3.55	0.724
	Stdev.	0.91	0.95	1.08	0.92	
Perceived usefulness of technology (PU)	Av.	3.70	3.79	3.29	3.71	0.218
	Stdev.	0.79	0.88	0.99	0.80	

For statistically significant differences at the 0.05 level, values given in boldface are the largest and those in italics are the smallest.
[*] Indicates the variables that differ between the three groups at the 10% level of significance.
[**] Indicates the variables that differ between the three groups at the 5% level of significance.
[***] Indicates the variables that differ between the three groups at the 1% level of significance.

4.2. Non-traders

In total, there were 48 (10.9%) respondents who always selected the EV as their best/preferred alternative and a further 24 (5.5%) respondents who always placed EV as their worst/least preferred alternative. Table 1 shows that socio-demographics were not significantly different between the two groups, although the EV non-traders (Best) were generally younger and more highly educated. In contrast, EV non-traders (Worst) were generally older, earn about 24k more than the rest of the sample, and are willing to spend around 12k more for their next car compared to respondents who traded the EV characteristics.

However, what distinguishes between EV non-traders (Best), EV non-traders (Worst), and the rest of the sample is their significantly different predisposition to buy EV as their next car (3.77 for EV non-traders Best vs 2.70 for traders and 1.50 for EV non-traders Worst), the perception that their travel needs could be satisfied without a second car with ICE (3.54 for EV non-traders Best vs 2.87 for traders and 1.58 for EV non-traders Worst), and their stated frequency of using EV if they owned one (4.15 for EV non-traders Best, 3.55 for traders, and 2.5 for EV non-traders Worst).

Similarly, comparison of latent constructs indicates significantly higher 'Environmental concerns' and 'Subjective norms' for EV non-traders Best (2.85 and 3.40), compared to 2.65 and 2.72 for respondents who traded the attributes of the experimental design. Perhaps unsurprisingly, the lowest attitudinal scores were recorded for the EV non-traders Worst (2.21 and 2.35). EV non-traders Worst also displayed the lowest scores for 'Excitement for new technologies' (3.20) and 'Perceived usefulness of the EV technology' (3.29). The pattern of consistently lower values for all four attitudinal constructs displayed by the EV non-traders Worst suggests that different motivations and decision mechanisms may influence their choice for EV technologies.

4.2.1. Additional best and worst non-trading insights

A further insight into the non-trading behaviour is made by observing the choices made for the Worst alternative, as well as the choice of Best. It is noted that 39 respondents also did not trade when it came to selecting the Worst vehicle, and 46 respondents were non-traders both on Best and Worst alternatives. Perhaps these respondents used a predetermined ranking which was unaffected by the attribute levels. They seem to face the decision of purchasing a new vehicle later than the other respondents (3.54), they are less likely to buy an EV (2.72) and less likely to satisfy their mobility needs without an ICE car (2.63). The 13 Petrol non-traders also exhibit non-trading behaviour when selecting the worst option in the choice sets. Their choice data may be indicative of a degree of distrust for alternative fuel and vehicle technologies.

With other non-trading responses it is not always clear to establish the motivation behind them. Whereas some respondents may be non-traders, others may have been disengaged with the task and used non-trading as a means to hasten their responses. Compounding this explanation is that there was a reward on offer for completed surveys and non-trading may have been a strategy for completing the task quickly and without much thought. Non-trading may have also occurred due to inadvertent design issues with the survey itself. The four alternatives (EV, Petrol, Plug-in Hybrid and Diesel) were presented in the same sequence for both the web-based and the paper-and-pencil version; this might have misled the respondent to choose EV more often than the other alternative simply by design. Finally, a respondent may have used compensatory decisions, but none of the presented choice sets had attribute levels that would have caused a switch from their preferred alternative. Although the purpose of experimental designs is to present sufficient attribute variation to prevent non-trading, some respondents may simply always exhibit extreme preferences.

Given the degree of non-trading present in this dataset, the following analysis investigates possible causes for the non-trading behaviour of respondents who selected EV only. A joint Best-Worst choice model is proposed to overcome some of the challenges presented by non-trading behaviour in choice experiments.

5. Determinants of electric vehicle stated choice

5.1. Investigating the role of subjective norms and environmental concerns in the choice of EV

The choice model for the SC panel is estimated using a random effects panel model. Effectively this is achieved by estimating a random parameter for alternative specific constants (ASC) that are perfectly correlated over the choice scenarios for each individual. The latent factor scores from the confirmatory model enter the utility expressions as variables. An error component is introduced to capture the correlations between Hybrid and Electric Vehicles (EV) as they represent different refuelling technologies and are relatively new on the Australian market. Similarly, an error component is introduced to capture any correlations between Diesel and Petrol. A parameter for each treatment in the experiment is reported, whether it is significant or not. The purpose of the results in Table 2 is to investigate the impact on the parameters due to retaining the EV non-traders. A separate model is estimated for each source of data.

The panel data random effects choice model was run for a sample that included the 48 EV non-traders (N = 399) and another only for the identified traders (Best, N = 351). Each model uses a simulated maximum likelihood estimater with 150 draws from a Halton sequence. Parameter stability was noted for draws of between 50 and 100, but we reported the model with the highest number of draws. The estimation of two separate models was undertaken because other modelling techniques to test the parameter difference between two sub samples are not possible using non-trader sub-samples. Creating interactions with attributes will not work because the interaction parameter will be perfectly correlated with a subset that only chooses this alternative and the maximum likelihood has no turning point. The same issue would be faced if attempting to interact a non-trading identifier with the mean of a random parameter.

For most parameters there is no significant difference between the estimated means presented in Table 2; the exception being the estimated standard deviations of the random effect parameters. These differences are to be expected, because the random effects for non-traders need to take into account the respondents' increased propensities to selecting a particular alternative irrespective of the attribute levels. The other two parameters of interest are the latent constructs of SN and EC. The 'Environmental concerns' EC is significantly different over the two samples (p-value = 0.050), but the evidence about 'Subjective norms' SN is less clear (p-value = 0.115). The parameter estimate for the interaction between gender and the Diesel ASC (Male $*$ Diesel) is significantly different when the estimation sample is for traders only (p-value <0.05).

Two choice models of the respondents' least preferred alternatives (Worst) are listed on the right hand side of Table 2. The first model includes respondents that exhibited trading behaviour when selecting their least preferred option, as well as the 24 respondents who selected the EV only. The two latent constructs – EC and SN – are neither significant, nor do they differ significantly across the two samples. It would seem that for at least part of the sample, the desire to express higher than average concern for the environment translates into non-trading behaviour (Best). This association may be explained by the respondents' higher concern for how other people view their behaviour with respect to vehicle purchases (SN). However, the relationship between non-trading behaviour and higher EC or SN does not seem to play a part when selecting the Worst alternative.

The results from these models seem to indicate that willingness-to-pay estimates, being functions of the parameters on the attribute treatments, will not be greatly affected by the retention of the non-traders, however, forecasting using these results will be. Whilst it would not be advisable to use these data for forecasting the uptake – the estimates are not conditioned on real market data – there remains the issue of forecasting in the presence of non-traders. Should the respondents truly be non-traders and will only buy an EV on their next purchase, then they can be removed from the choice analysis and added back to the expected market share forecast as being an additional segment of the population who purchase an EV.

Table 2
Choice model results for the best and the worst data.

Variable	Best only Traders (N = 351) + EV non-traders (N = 48)		Best only Traders (N = 351)		Worst only Exhibiting trading choices (N = 305) + selecting EV only (N = 24)		Worst only Exhibiting trading choices (N = 305)	
	Par.	Asympt. Z value	Par.	Asymt. Z value	Par.	Asympt. Z value	Par.	Asympt. Z value
Random effects								
ASC EV	0.150	0.42	0.751	0.44	0.190	0.08	0.261	0.11
ASC petrol	**0.579**	2.71	**0.531**	2.71	−0.366	−1.97	−0.351	−1.81
ASC plug-in-hybrid	**2.894**	6.50	**2.766**	5.59	−0.919	−1.81	0.791	−1.47
St. dev. of random effects								
ASC EV	**1.808**	11.32	**1.206**	7.51	**2.047**	8.62	**2.097**	8.41
ASC petrol	**1.926**	12.79	**1.153**	7.14	**0.979**	9.04	**0.989**	8.74
ASC plug-in-hybrid	**1.783**	10.38	**1.318**	8.14	**0.956**	4.18	**0.981**	4.14
Error components								
EV and plug-in-hybrid	0.240	1.25	0.469	1.82	0.936	4.49	0.904	4.15
Petrol and diesel	**1.384**	8.40	**0.936**	4.79	0.305	1.00	0.281	0.99
Attributes presented in the SC experiment								
Price	−**0.065**	−8.96	−**0.061**	−8.24	−**0.080**	−5.2	−**0.083**	−5.25
Running cost	−**0.259**	−9.08	−**0.253**	−8.81	−**0.270**	−5.69	−**0.246**	−4.87
EV-range	−**0.012**	−3.32	−**0.012**	−3.35	−0.003	−0.35	−0.004	−0.42
GHG	0.040	0.80	0.050	0.98	**0.265**	4.09	**0.255**	3.35
Noise	−**0.391**	−6.71	−**0.400**	−6.89	−**0.403**	−3.91	−**0.407**	−3.83
Charging time	−**0.004**	−5.64	−**0.004**	−5.62	−**0.008**	−4.7	−**0.008**	−4.72
Battery capacity	0.364	0.21	−0.197	0.12	1.898	0.46	1.599	0.38
Range	$0.9 * 10^{-4}$	0.52	$0.9 * 10^{-4}$	0.75	0.001	1.1	0.001	0.85
Engine size	**1.386**	6.66	**1.273**	5.98	0.444	1.26	0.261	0.72
Interactions								
EV * environmental concerns	**1.220**	4.58	**0.730**	3.04	−0.091	−0.25	−0.193	−0.55
EV * social norms	**0.406**	5.18	**0.280**	3.18	−0.008	0.05	−0.011	−0.07
Environmental concerns * GHG	−0.018	−0.95	−0.023	−1.15	−**0.120**	−5.32	−**0.106**	−4.00
Male * diesel	**1.386**	5.55	**0.651**	4.41	0.026	0.17	−0.057	−0.36
Model statistics								
LL Model	−2759.92		−2469.08		−1944.26		−1797.82	
LL ASC's	−3751.31		−2994.39		−2851.61		−2610.39	
McFadden's pseudo r^2	0.264		0.1754		0.318		0.311	
AIC/N	2.055		2.306		1.911		1.932	

Note: Par. = parameter estimate; Asympt. = asymptotic Z value (absolute values greater than 1.65 mean parameter is significant at 0.1 level; $|Z| > 1.96$ indicates sig. at the 0.05 level and $|Z| > 2.35$, sig. at the 0.01 level). In bold, parameters significant at 0.01 level.

However, these data suggest that the non-trading behaviour may be rather due to a social desirability or demand characteristic effect in addition to non-attendance.

5.2. A joint model of best-worst choice data in the presence of non-trading

Whilst the non-traders do not seem to affect the parameter estimates on the attributes presented in the stated choice experiment, it was deemed agreeable to remove their (Best) choice data from the modelling set. However, as is noted in the model of the Worst data, these respondents do not systematically differ from the traders within the sample. Rather than disregarding all the choice data for the non-traders, the models below are based on the retained Worst choice data for the non-traders.

A similar approach is taken for the respondents who exhibited non-trading behaviour for the Worst choice data, but appeared to trade attributes when choosing their Best alternative. However, in this case it is thought that non-trading when selecting their Worst alternative is an indication that they rule this option out of their choice set. The choice data for the Best is estimated on the three remaining vehicle technologies. For example, if a respondent had always chosen the EV as their least preferred, then EV is removed from the choice set for their most preferred. We removed the respondents who did not exhibit trading behaviour when selecting their most (Best) and least preferred (Worst) alternatives. However, as noted before, some of these respondents may have been exercising a legitimate choice. The respondents who chose Petrol only, always selected one of the three remaining alternatives as their least preferred. It would seem these respondents had a predetermined order of preference that was independent of the attribute levels presented in the survey instrument. All remaining traders (Best and Worst) were retained.

Table 3
A joint best-worst random effects and error component choice model in the presence of non-traders.

Variable	Best choice data N = 290 traders best and worst N = 61 traders best only		Worst choice data N = 290 traders best and worst N = 39 traders worst only	
	Par	Asympt. Z value	Par	Asympt. Z value
Random effects				
ASC EV	1.530	0.97	−**2.008**	−2.44
ASC petrol	**0.597**	3.10	−**0.419**	−3.53
ASC plug-in-hybrid	**2.605**	5.83	−**1.565**	−5.96
St. dev. of random effects				
ASC EV	**1.111**	6.95	**1.967**	8.24
ASC petrol	**1.128**	7.12	**1.087**	9.67
ASC plug-in-hybrid	**1.235**	7.65	**1.060**	4.60
Error components				
EV and plug-in-hybrid	**1.062**	6.24	0.279	1.11
Petrol and diesel	0.205	0.49	**0.796**	3.43
	Jointly estimated parameters for the attributes presented in the B-W stated choice experiment. Scale parameter for worst = 1.72			
	Par		Asympt. Z	
Attributes presented in the SC experiment				
Price	−**0.068**		−10.42	
Running cost	−**0.267**		−11.21	
EV-range	−**0.011**		−3.22	
GHG	**0.100**		2.42	
Noise	−**0.394**		−8.23	
Charging time	−**0.005**		−7.07	
Battery capacity	−0.233		−0.15	
Range	0.001		1.33	
Engine size (best only)	**1.155**		6.72	
Interactions				
EV * environmental concerns ASC	0.355	1.48	–	–
EV * social norms ASC	**0.298**	3.35	–	–
Environmental concerns * GHG	−**0.039**	2.43	−**0.065**	4.18
Male * diesel ASC	**0.613**	3.73	–	–
Model statistics				
LL model	−4376.03			
LL ASC's	−8818.91			
McFadden's pseudo r^2	0.504			
AIC/N	2.078			

Note: Par. = parameter estimate; Asympt. = asymptotic Z value (absolute values greater than 1.65 mean parameter is significant at 0.1 level of confidence; |Z| > 1.96 indicates sig. at 0.05 level and |Z| > 2.35, sig. at 0.01 level. In bold, parameters significant at 0.01 level.

In summary, the estimation of a joint Best-Worst stated choice model, presented in Table 3, meant selecting a sample from those who exhibited trading in one or the other data set. A random effects choice model was also adopted here. However, because of the two sources of data (Best and Worst) a scale parameter of 1.752 was used to rescale the Worst data. Whilst a full information maximum likelihood estimator would be more appropriate, the model failed to converge and instead a preliminary nested logit (NL) model was estimated and the variables were rescaled before the estimation of this joint Best and Worst model. Most of the attributes of the vehicles are estimated jointly using the Best and the rescaled Worst data, except Engine size, which is estimated on the Best choice data only. The two error components for each data set and the interactions between attitudes and the ASC's were retained. However, the interaction between environmental concerns (EC) and greenhouse gas emissions (GHG) had a parameter estimated for each data set.

The results in Table 3 indicate that the respondents take into account the purchase price (Price) of the vehicle as well as its Running cost. However, the impact of driving range on the choice of the electric vehicle (EV-Range) has an unexpected sign. Larger engines (non-EV alternatives) are attractive, as are less noisy vehicles. Despite removing the non-traders from the estimation sample, higher subjective norm scales are still associated with the choice of EV (Best). Also, the respondents who strongly believe *"People who are important to me or people that influence me think that that I should buy an EV"*, tend to choose the EV alternative more often than those scoring lower on this scale.

The results also suggest substantial preference heterogeneity and the inclusion of the latent scores for EC and SN in the alternative specific constants for the EV changes their location towards substantially higher values, potentially reflective of the environmental enthusiasm for EV. Whilst Environmental concerns (EC) was significant in the Best only model, the association was less conclusive in the joint B-W choice model. Nevertheless, the interaction between GHG emissions and EC was significant for both the Best and Worst choice data. This would indicate that the respondents are responding to the environmental performance of the vehicle rather than simply selecting the 'environmentally friendly' alternative.

6. Conclusion

The paper examines possible response bias as being the cause of non-trading in a Best-Worst SC experiment focused around EV choice in Western Australia. The first point of note is that, in line with a priori expectations, levels of non-trading were high, with 10.9% of the 440 participants always selecting the EV as their most preferred (Best) option and 5.4% always selecting the EV as least preferred (Worst) across all choice replications. Comparisons of the two groups revealed that while there were no significant demographic differences, the EV non-traders (Best) scored significantly higher on constructs designed to capture their 'Environmental concerns' and 'Subjective norms', while the EV non-traders (Worst) scored significantly lower on these constructs. While it is possible that non-trading occurred due to so-called 'demand' effects in which some participants may have responded in a way they perceived the experiment wanted them to, or due to other design issues with the survey, it appears unlikely based on these findings.

The choice results were inconclusive on the actual cause of the non-trading, but the associations between stated behaviour and 'Environmental concerns', along with 'Subjective norms', were weaker when the non-traders were removed. In addition, the association between the attitudinal latent variables and the choice of the least preferred alternative were insignificant. Respondents who scored low on 'Subjective norms' or held lower than average 'Environmental concerns' were not *on average* selecting the electric vehicles as the Worst option. The results of the joint Best-Worst choice model indicated that 'Subjective norms' are associated with the selection of an electric vehicle (Best), but Environmental concerns were associated with the environmental performance of the vehicles, rather than just the label.

Regardless of the respondents' motivations for non-trading, this research suggests that WA residents, particularly EV enthusiasts, may not be as concerned with the range of the EV as they are with the recharging infrastructure available and the perceived environmental benefits of EV technology. More attention needs to be paid to sample selectivity, response bias and survey design and ultimately the results of the estimated choice models. Despite the absence of an interviewer, the mail-out survey of the type used here seemed to attract a biased sample of an *interested* segment of the community. It is suggested that different survey mechanisms may be more appropriate when the context lends itself to social desirability, such as the one under investigation. Even when data sampling strategies are followed closely to ensure representativeness of the population, these are generally focused on socio-demographics and spatial coverage. Our results show that attitudes need to get a more prominent role in filtering and controlling for social desirability apriori. Additional investigation is warranted in the introduction of a social desirability test, before answering a survey, to limit the magnitude of non-trading behaviour in stated choice experiments. Asking respondents to answer a certainty and/or desirability scale question at the end of the survey would also assist in characterising the non-trading behaviour. As in this research the magnitude of non-trading was not anticipated, our strategy to address non-trading behaviour was to use a Best-Worst design, instead of a Best only choice stated preference.

Accepting there may be various reasons behind the observed non-trading behaviour (Hess et al., 2010), the analysis provides insights on characteristics of potential adopters of EVs in (Western Australia). Indicators here suggest that EV adopters are more likely to be younger, more educated and male, although the fact these are not statistically significant suggests that socio-demographics in themselves may not be a key explanatory variable. The more relevant issues that emerged here revolved around attitudes towards (in this case) the environment, technology, and implicitly a perception that mobility needs can be met. This may be indicative of an environmental enthusiasm bias in the sample, unlikely to represent the general population. In this sense, the relatively high values of the latent scores may be considered as a diagnostic tool for benchmarking sample respondents against the population average to identify potential non-traders.

From a modelling perspective, it was noted that despite the propensity of a proportion of respondents to choose EV as their Best across all experiments, it was possible to recover information about their preference for vehicle attributes by retaining their Worst choice. The possible explanation of non-trading (Best) being the desire of respondents to present themselves as environmentally friendly to others as indicated by their comparatively higher scores on the EC and SN constructs. The relationship between non-trading (Worst) and attitudinal scores was not reflected in the Worst data set. By deploying a survey that enabled capturing choice data on both the Best and the Worst alternatives, the final Best-Worst model was able to be estimated on observations that may have been discarded with Best only data.

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Appendix A

A.1. Attributes and levels used in experimental design

Attribute	Alternative	Number of levels	Values for mail-out sample
Engine size (L)	Generic	3	1.6; 2.0; 2.4
Range (km)	EV	3	100; 120; 140
	Plug-in hybrid	3	400; 500; 600 (including 30 min of home-charging)
	Petrol	3	600; 700; 800
	Diesel	3	800; 900; 1000
Running cost ($/100 km)	EV	3	1.4; 1.7; 2.0
	Plug-in hybrid	3	4; 5; 6
	Petrol	3	7.5; 10.0; 12.5
	Diesel	3	6.0; 7.5; 9.0
Purchase price ('000 $)	EV	3	34; 42; 50
	Plug-in hybrid	3	37; 45; 53
	Petrol	3	28; 36; 44
	Diesel	3	30; 38; 46
Greenhouse gas GHG emissions (kg/100 km)	EV	3	11; 12; 13
	Plug-in hybrid	3	13; 15; 17
	Petrol	3	21; 26; 31
	Diesel	3	21.0; 23.5; 26.0
Noise	EV	N/A	0 (no noise)
	Petrol, diesel, plug-in hybrid	3	1; 2; 3 (low to high)
Charging time (h)	EV	3	0.2; 1.5; 4.0
	Plug-in hybrid	N/A	N/A
	Petrol/diesel	N/A	N/A
Battery capacity after 10 years	EV, plug-in hybrid	3	85%; 90%; 95%
	Petrol/diesel	N/A	N/A
Number of fast charging stations (types 2 and 3)	EV	3	500; 1000; 1500
	Plug-in hybrid	N/A	Charging at home
	Petrol/diesel	N/A	N/A

A.2. Construct items in confirmatory factor analysis: mail out sample (n = 440)

Constructs	Items	Loadings/ estimates	Error variance	Model fit	% Variance
Environmental concern (EC)	*Saving the environment requires our immediate efforts*	0.876	0.193	GFI = 0.999 RMR = 0.005 $X^2(1) = 0.483$; p = 0.487	46
	I am concerned that future generations may not be able to enjoy the world as we know it currently	0.595	0.141		

(*continued on next page*)

Appendix A.2 (*continued*)

Constructs	Items	Loadings/ estimates	Error variance	Model fit	% Variance
	Climate change is a myth	−0.404	1.456		
	Now is high time to worry about the effects of air pollution	0.919	0.695		
Perceived usefulness of technology (PU)	*I love gadgets*	0.485	1.097	GFI = 0.998 RMR = 0.023 $X^2(2) = 1.448$; p = 0.485	35
	Using new technologies makes life easier	0.622	0.536		
	I use online maps to plan my travel when I need to visit a new place	0.586	1.131		
	Exploring new technologies enables me to take benefit from latest developments	0.819	0.285		
Subjective norm (SN)	People who are important to me think that I should buy an EV	0.91	0.122	GFI = 0.999 RMR = 0.004 $X^2(1) = 0.571$; p = 0.450	53
	I would buy an EV if many of my friends would use an EV	0.689	0.204		
	Being fashionable means having up to date knowledge of this techno-world	0.465	1.096		
	People who influence my behaviour think I should buy an EV	0.944	0.674		
Excitement for new technologies (ENT)	*Keeping my knowledge up to date about technology is necessary*	0.681	0.471	GFI = 0.988 RMR = 0.025 $X^2(3) = 13.8$; p = 0.003	53
	I enjoy the challenge of figuring out high-tech gadgets. (re-worded)	0.719	0.529		
	I prefer to use the most advanced technology available	0.811	0.257		
	I am excited to learn new technologies	0.875	0.44		
	New technologies enable me to resolve my daily tasks. (re-worded)	0.656	0.82		

Note: Only 17 indicators were used in these four constructs. Two additional constructs on 'Ease of use' and 'Perceived barriers' displayed low construct reliability.

References

AECOM, 2009. Economic Viability of Electric Vehicles. Prepared for New South Wales Department of Environment and Climate Change.

Armitage, C.J., Conner, M., 1999. Predictive validity of the theory of planned behaviour: the role of questionnaire format and social desirability. J. Commun. Appl. Soc. Psychol. 9 (4), 261–272.

Armitage, C.J., Conner, M., 2001. Efficacy of the theory of planned behaviour: a meta-analytic review. Br. J. Soc. Psychol. 40 (4), 471–499.

Auger, P., Devinney, T., Louviere, J.J., 2007. Using best-worst scaling methodology to investigate consumer ethical beliefs across countries. J. Bus. Ethics 70 (3), 299–326.

Azjen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211.

Bailey, H., Miele, A., Axsen, J., 2015. Is awareness of public charging associated with consumer interest in plug-in electric vehicles? Transport. Res. Part D: Transport Environ. 36, 1–9.

Bolduc, D., Boucher, N., Alvarez-Daziano, R., 2008. Hybrid choice modeling of new technologies for car choice in Canada. Transp. Res. Rec. 2082, 63–71.

Bonsall, P., 2009. What is so special about surveys designed to investigate the environmental sustainability of travel behaviour? In: Bonnel, P., Lee-Gosselin, M.E.H., Zmud, J., Madre, J.-L. (Eds.), Transport Survey Methods: Keeping Up with a Changing World. Emerald, Bingley, UK, pp. 49–69.

Brenner, P.S., DeLamater, J.D., 2014. Social desirability bias in self-reports of physical activity: is an exercise identity the culprit? Soc. Indic. Res. 117 (2), 489–504.

Bühler, F., Franke, T., Cocron, P., Schleinitz, K., Neumann, I., Ischebeck, M., Ktrems, J.F., 2014. Driving an EV With No Opportunity to Charge at Home – Is This Acceptable? <http://www.hfes-europe.org/wp-content/uploads/2014/06/Buehler.pdf>.

Caussade, S., Ortúzar, J. de D., Rizzi, L., Hensher, J. de D., 2005. Assessing the influence of design dimensions on stated choice experiment estimates. Transp. Res. Part B 39 (7), 621–640.

ClimateWorks, 2016. The Path Forward for Electric Vehicles in Australia. <http://climateworks.com.au/sites/default/files/documents/publications/the_path_forward_for_electric_vehicles_in_australia_-_submission_to_the_federal_government_vehicle_emissions_discussion_paper_0.pdf>.

Cohen, E., 2009. Applying best-worst scaling to wine marketing. Int. J. Wine Bus. Res. 21 (1), 8–23.

Collins, A.T., Rose, J.M., 2013. Estimation of Stochastic Scale with Best-worst Data. ITLS Working Paper WP-13-13. ISSN 1832–570X. <http://sydney.edu.au/business/__data/assets/pdf_file/0020/173603/ITLS-WP-13-13.pdf>.

Cook, J., Jeland, M., Maskery, B., Whittington, D., 2012. Giving stated preference respondents "time to think": results from four countries. Environ. Resour. Econ. 51, 473–496.

Crowne, D.P., Marlowe, D., 1960. A new scale of social desirability independent of psychopathology. J. Consul. Psychol. 24 (4), 349.

Dagsvik, J.K., Wennemo, T., Wetterwald, D.G., Aaberge, R., 2002. Potential demand for alternative fuel vehicles. Transp. Res. Part B 36, 361–384.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quart. 13, 319–340.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: an analysis of consumer attitudes and perceptions. Energy Policy 48, 717–729.

Ewing, G., Sarigollu, E., 2000. Assessing consumer preferences for clean-fuel vehicles: a discrete choice experiment. J. Publ. Policy Mark. 19, 106–118.

Fifer, S., Rose, J., Greaves, S., 2014. Hypothetical bias in stated choice experiments: is it a problem? And if so, how do we deal with it? Transp. Res. Part A 61, 164–177.

Figenbaum, E., Kolbenstvedt, M., Elvebakk, B., 2014. Electric Vehicles – Environmental, Economic and Practical Aspects As Seen by Current and Potential Users. TØI Report 1329/2014.

Finn, A., Louviere, J.J., 1992. Determining the appropriate response to evidence of public concern: the case of food safety. J. Publ. Policy Mark. 11 (2), 12–25.

Flynn, T.N., Louviere, J.J., Peters, T.J., Coast, J., 2007. Best–worst scaling: what it can do for health care research and how to do it. J. Health Econ. 26 (1), 171–189.

Flynn, T.N., Marley, A.A.J., 2014. Best-worst scaling: theory and methods. In: Hess, S., Daly, A. (Eds.), Handbook of Choice Modelling. Edward Elgar, UK, pp. 178–201 (Chapter 8).

Golob, T.F., Gould, J., 1998. Projecting use of electric vehicles from household vehicle trials. Transp. Res. Part B 32 (7), 441–454.

Guo, J., Qiu, M., 2010. A latent class approach for modelling driver preferences in new in-vehicle information system design. Papers of the European Conference on Human Centred Design for Intelligent Transport Systems, vol. 1. ECHCDIT, Lyon, pp. 97–110.

Heffner, R., Kurani, K., Turrentine, T., 2007. Symbolism in California's early market for hybrid electric vehicles. Transp. Res. D 12, 396–413.

Hensher, D.A., 2010. Hypothetical bias, choice experiments and willingness to pay. Transp. Res. Part B 44 (6), 735–752.

Hess, S., Rose, J.M., Polak, J., 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. Transp. Res. Part D 15 (7), 405–417.

Hess, S., Train, K.E., Polak, J.W., 2006. On the use of a modified Latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. Transp. Res. Part B 40, 147–163.

Hidrue, M.K., 2010. The Demand for Conventional and Vehicle-to-grid Electric Vehicles: A Latent Class Random Utility Model. Doctoral Dissertation. UMI Number: 3440476.

Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33, 686–705.

Holbrook, A.L., Krosnick, J.A., 2010. Social desirability bias in voter turnout reports. Publ. Opin. Quart. 74 (1), 37–67.

Jensen, A.F., Cherchi, E., Ortúzar, J. de D., 2014. A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. Transportation 41 (5), 973–993.

Kim, J., Rasouli, S., Timmermans, H., 2014. Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: application to intended purchase of electric cars. Transp. Res. Part A 69, 71–85.

Krumpal, I., 2013. Determinants of social desirability bias in sensitive surveys: a literature review. Qual. Quant. 47 (4), 2025–2047.

Kurani, K.S., Turrentine, T.S., Sperling, D., 1996. Testing electric vehicle demand in hybrid households' using a reflexive survey. Transp. Res. Part D 1, 131–150.

Lee, Z., Sargeant, A., 2011. Dealing with social desirability bias: an application to charitable giving. Eur. J. Mark. 45 (5), 703–719.

Leroy, G., 2011. Designing User Studies in Informatics. Springer, London.

Lieven, T., Mühlmeier, S., Henkel, S., Waller, J.F., 2011. Who will buy electric cars? An empirical study in Germany. Transp. Res. Part D 16, 236–243.

Lin, Z., Greene, D.L., 2011. Promoting the market for plug-in hybrid and battery electric vehicles. Transp. Res. Rec.: J. Transp. Res. Board 2252, 49–56.

Louviere, J.J., Woodworth, G.G., 1990. Best-Worst Scaling: A Model for Largest Difference Judgments. Working Paper, Faculty of Business, University of Alberta.

Lusk, J.L., Norwood, B., 2011. Social desirability bias in real, hypothetical, and inferred valuation experiments. Am. J. Agric. Econ. 93 (2), 528–534.

Marley, A.A., Louviere, J.J., 2005. Some probabilistic models of best, worst, and best–worst choices. J. Math. Psychol. 49 (6), 464–480.

Meuter, M.L., Ostrom, A.L., Bitner, M.J., Roundtree, R., 2003. The influence of technology anxiety on consumer use and experiences with self-service technologies. J. Bus. Res. 56 (11), 899–906.

McCambridge, J., de Bruin, M., Witton, J., 2012. The effects of demand characteristics on research participant behaviours in non-laboratory settings: a systematic review. PLoS ONE 7 (6), e39116. http://dx.doi.org/10.1371/journal.pone.0039116.

Nichols, A.L., Maner, J.K., 2008. The good-subject effect: investigating participant demand characteristics. J. Gen. Psychol. 135 (2), 151–166.

Norwood, B., Lusk, J.L., 2011. Social desirability bias in real, hypothetical, and inferred valuation experiments. Am. J. Agric. Econ. 93 (2), 528–534.

Orne, M.T., 1962. On the social psychology of the psychological experiment: with particular reference to demand characteristics and their implications. Am. Psychol. 17 (11), 776.

Ozaki, R., 2011. Adopting sustainable innovation: what makes consumers sign up to green electricity? Bus. Strat. Environ. 20, 1–17.

Parasuraman, A., 2000. Technology Readiness Index (TRI) a multiple-item scale tomeasure readiness to embrace new technologies. J. Serv. Res. 2 (4), 307–320.

Peters, A., Dütschke, E., 2014. How do consumers perceive electric vehicles? A comparison of German consumer groups. J. Environ. Planning Policy Manage. 16 (3), 359–377.

Ratchford, M., Barnhart, M., 2012. Development and validation of the technologyadoption propensity (TAP) index. J. Bus. Res. 65 (8), 1209–1215.

Rogers, E.M., 2003. Diffusion of Innovations. Free Press, New York.

Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transp. Res. Part A 48 (2), 39–49.

Venkatesh, V., Davis, F.D., 2000. A theoretical extension of the technology acceptance model: four longitudinal field studies. Manage. Sci. 46 (2), 186–204.

Weiner, I.B., Craighead, W.E. (Eds.), 2010. The Corsini Encyclopedia of Psychology, vol. 4. John Wiley & Sons, New Jersey.

Yang, K., 2012. Consumer technology traits in determining mobile shopping adoption: an application of the extended theory of planned behaviour. J. Retail. Consum. Serv. 19, 484–491.

Zaichkowsky, J., 1985. Measuring the involvement construct. J. Consum. Res. 12, 341–352.

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: a discrete choice analysis for Germany. Transp. Res. Part A 46 (8), 1372–1385.