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Electric Vehicles Adoption: Environmental Enthusiast Bias in Discrete Choice Models

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Abstract

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 for research, stated choice (SC) experiments have emerged as a popular tool to study the factors that influence the uptake of EVs. The assumption behind these experiments is that respondents make trade-offs on the attributes presented in the instrument.

As part of the Western Australian Electric Vehicle Trial (WAEVT), a stated choice survey was administered to 440 households in Perth. It was noted that 48 (10.9%) respondents chose the EV option as their best across all six stated choice replications. We hypothesise that for most of these respondents their choices reflect their desire to present themselves in a favourable light. In this instance the social desirability biasness manifests in non-trading behaviour. There were also 24 respondents who chose EV as their least preffered option. We hypothesise that for these respondents lack of interest or confidence in the new technology and inertia may have driven their decisions.

This paper offers a demographic and psychographic profile of the non-traders - made possible by items being added to the experiment. While there was little differences between the demographic profiles, there was some evidence from the attitudinal data that the non-trading was due to social desirability. Non-traders (Best) scored significantly higher on environmental concerns and subjective norms, were more likely to rate their intention to purchase and use an EV higher and chose EV in all choice sets, despite the experimentally controlled attributes. Conversely, non-traders (Worst) had the lowest environmental concerns and subjective norms.

From a choice modelling perceptive, keeping non-traders in the estimation biases the taste parameters and therefore the willingness-to-pay (WTP) measures. However, the choice tasks asked respondents to indicate their least preferred option as well as their best. When indicating the worst alternative 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

Electric vehicles (EVs) generate far less emissions in the city than conventionally powered motor vehicles (Nichols *et al*., 2015). In addition, there is potential for EVs to be powered by renewable sources (Saber & Venayagamoorthy, 2011). For these reasons the EV alternative is attractive to people whose values on the environment and social consciousness align with the social benefits of EV's.

Many Australian households use more than one car (ABS, 2008) so that the range limitation of EVs may not be considered an issue when there is a second car available for long distance trips. With their relatively lower operational costs (once purchased), EVs can be fully utilised for short trips within the city, but the need to recharge – rather than refill – requires good trip planning. Households will trade-off other attributes of the vehicles such as lower running cost, lower noise, lower emissions and the life of the battery against the relatively higher purchase cost of the EV. These elements are investigated through stated choice (SC) experiments where drivers and households were asked to compare a set of optimally designed scenarios with various vehicle and fuel alternatives (including the EV) and choose the preferred alternative. However, SC is not actual behaviour and as is the case for adoption models – technology adoption model (TAM) or theory of planned behaviour (TPB) – there may may be a distinct gap between stated intention and actual purchase behaviour. It is expected that SC methods have a higher degree of validity in that the description of the alternatives in a market are presented to the respondents. This requires a greater cognitive involvement in the task as compared to responding to: *“would you buy an electric vehicle?”*

Putting aside the issue of face validity, SC experiments are self-reported questionnaires of stated intention. In addition, as hybrid choice models become more the norm rather than the exception, SC experiments are also surveys of attitudes, social norm constructs and self perceptions. As such they are subject to a number of response biases – including demand characteristics and social desirability. In this paper we identify 48 respondents from the Western Australian Electric Vehicle Trial (WAEVT) who selected EV only as best across six choice tasks and 24 who selected EV as their worst option. In a situation where respondents choose one alternative as best case in all given choice sets, Hess *et al.* (2010) refer to this as non-trading behaviour that may occur in labelled choice experiments. In this study, respondents who selected EV in all choice tasks were identified and separated from the choice data. It is possible that the non-trading responses were made to present themselves as environmentally friendly to others (including the surveyor). In this case, the responses are subject to social desirability bias. The other possibility is that the respondents were attempting to understand the purpose of the experiment and unconsciously 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’ (Nichols & Maner, 2008).

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 & 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.

2. Literature Review

2.1 Electric Vehicle Adoption

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 Japan and the U.S. 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, with an EV market share of 0.04% as of 2014. Price remains a major barrier, with few meaningful incentives around the initial purchase of the vehicle or on-going costs (AECOM, 2011). However, recently prices have begun to fall, which will likely accentuate the importance of

[1] http://www.abb-conversations.com/2014/03/electric-vehicle-market-share-in-19-countries/. Accessed 25/2/15

other known barriers to wider EV adoption, primarily around ‘range-fear’ and recharging requirements (Lin & Greene, 2011).

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 1990’s in California (Kurani *et al.,* 1996; Golob & 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 & Sarigollu, 2000; Egbue & Long, 2012; Peters & Dütschke, 2014; Bailey *et al.,* 2015). These studies have identified the main EV market influences as the price, increase in range of the vehicle, fast charging and improved charging infrastructure, along with awareness about EV characteristics, environmental benefits, and EV readiness.

Most of these investigations have used SC approaches given the limited opportunities to study EV adoption in real markets. Bolduc *et al.* (2008) followed Kurani *et al.* (1996) and Ewing & Sarigollu (2000) in using attitudinal data and 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; capital cost, operating cost, fuel available, and emissions data were the main attributes. 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 set, particularly environmentally friendly aspect, 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 model (LCM) to explore EV acceptance. They found that savings in the fuel costs tended to lead to the purchase of EV; 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 *et al.* (2011) 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.

What really makes EV a contemporary new technology is the development of EV infrastructure. 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 Ajzen (1991); or diffusion of innovation theory (Rogers, 2003). Schuitema *et al.* (2013) and Egbue & Long (2012) applied TPB, and Ozaki & Sevastyanova (2011) applied diffusion of innovation theory for EV/hybrid vehicles adoption.

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 EV 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).

2.2 Best-Worst Choice Experiments

Best-worst choice analysis was developed by Louviere and Woodworth (1990) and, as described in its first application (Finn & Louviere, 1992), the best-worst (B-W) scaling allows for richer information. For a set of three alternatives, B-W provides a complete ranking, whereas with four alternatives, a partial ranking can be achieved. As shown by several recent studies in marketing (Cohen, 2009; Auger *et al.*, 2007) and health economics (Flynn *et al.*, 2007), best-worst 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 & Rose (2013) found that scale may vary across individual ranking; considering this observation they analysed a difference in scale across best or worst option chosen by respondents.

In terms of data set-up, the B-W data can be "exploded" in two alternative ways:

- By comparing the best option (i.e. the choice) with all the other alternatives, then after removing the best alternative, comparing the remaining options (chosen alternatives) with the worst alternative; this is termed an exploded logit data setup;
- By creating two choice situations, one with the choice being the best option and another with the choice being the worst option. This is termed a B-W or Best-Worst data setup.

2.3 Response Bias

As mentioned in the beginning of this paper, respondents who selected the same vehicle as their most or least preferred choice in all choice experiments are termed as non-traders. This paper further investigates the reasons or causes of this non-trading behaviour by respondents, particularly EV non-traders. With an invitation to participate in this study respondents were given a brief overview about Electric Vehicles in the form of a flyer with a description about EV distinct characteristics. Considering the fact that EV non-traders participated in this survey more with a purpose of highlighting their interest in Electric Vehicles, by looking at EV brochure, followed by choice scenarios, they picked EV to indicate their social desirability for EVs to the surveyor; this is further supported by their participation in the survey. Non-traders seem to have neglected vehicle attributes in experimental setting, and rather focused to indicate EV alternative as their most preferred choice in all experiments. Another thing to note here is that in these choice experiments four alternatives (EV, Petrol, Plug-in Hybrid and Diesel) were always presented in the same sequence for both the web-based and the paper-and-pencil version; this might also mislead the respondent to choose EV. In addition, EV non-traders reflected pro-environmental attitudes, again informing their positive attitude towards EV; with high scores for subjective norm as it contained EV in the items, for example "*I would buy an EV if many of my friends would use an EV*."; and also rated high intentions to purchase and use an EV – this clearly indicates their social desirability to present their acceptability towards electric vehicles. In doing so, EV non-traders ignored the vehicle attributes, such as EV's high purchase price, because EV were almost non-existent in the market at the time survey was conducted or because of the limited driving range barriers.

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 & 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, 2012).

In a psychology study examining the effect of having knowledge of a study’s hypothesis on the subject behavior 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 toward the experiment and experimenter. More positive attitudes meant more good-subject responses. But negative relations were found between socially desirable responding and reactions to participant demand (p. 161).

In their 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 go on 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

As already indicated, respondents may feel an underlying incentive to report more favourably centain attitudes and behaviours (Bonsall, 2009; Leroy, 2011). Many studies found that this effect was exacerbated by the interviewer’s resence. 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 impact of this effect is yet to be determined. It 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 assement (e.g., social desirability scale, Weiner & Craighead, 2010).

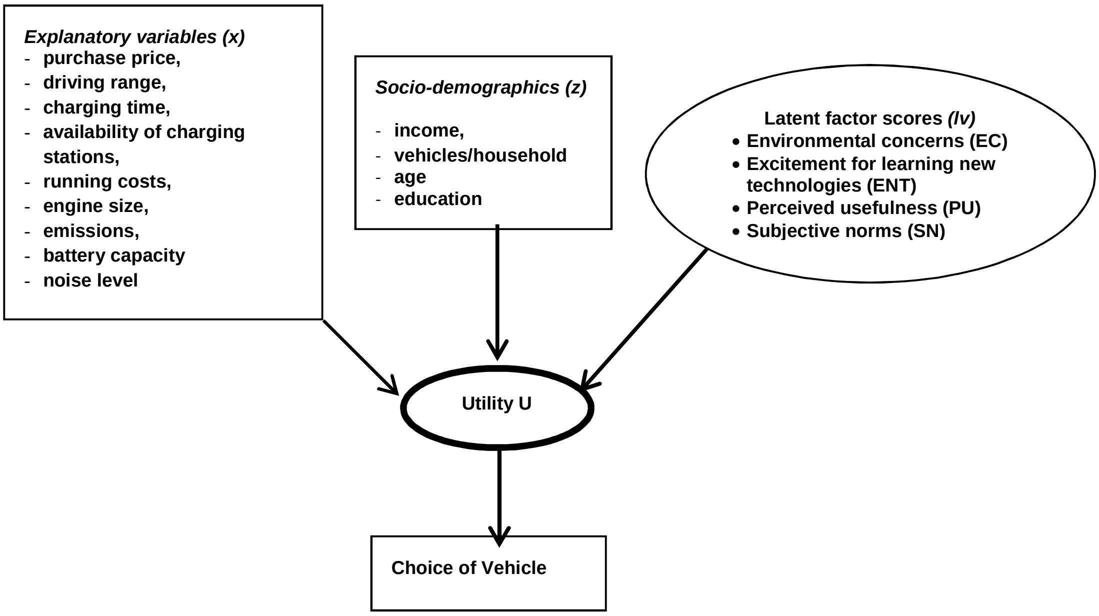
However, Armitage and Conner (1999) found no moderating effect of social desirability on relationships between TPB components, thus they supported the use of TPB predicting intentions and behaviour; while in another study, perceived behaviour control independently predicted intentions and behaviour (Armitage & 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 Figure 1. This brings together the explanatory variables, such as purchase price and range, with the latent variables, and the stated purchase decision. Unlike TAM (where behaviour is defined indirectly, by intentions), in this study individual behaviour is defined through choice and attitudinal data. 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 both attributes of the alternatives and characteristics of individuals, as well as the attitudinal data in the utility specification.

Figure 1: Conceptual Model



The attitudinal dimensions that were chosen are: i) *Environmental concerns (EC);* ii) *Excitement for new technologies (ENT);* iii) *Perceived usefulness (PU);* iv) *Subjective norms (SN)*.

Environmental concern attitude has already been used by a large number of studies that explore EV adoption behaviour (Ewing & Sarigollu, 2000; Dagsvik *et al*., 2002; Hidrue *et al*., 2011; Bolduc *et al*., 2008; Ozaki, 2011). 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 these two are derived from the diffusion of innovation theory, product involvement, and technology adoption scales (Rogers, 2003; Zaichkowsky, 1985; Yang, 2012).

3.2 Identifying Non-Traders

Non-trading is when a respondent chooses one alternative as best case in all given choice sets 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. It is however, not possible to determine a posteriori, the real cause for the respondent's behaviour without a follow-up interview. As this was not achievable in the study, in order to avoid errors in the valuation of attributes, data analysis was also carried out without non-trading observations, that is traders and non-traders in this study were compared. This paper focuses on the 48 respondents who always selected the EV and a further 24 respondents who always placed EV as their worst alternative.

4. Empirical Inquiry

4.1 Summary Stats for Sample

As part of the Western Australian Electric Vehicle Trial (WAEVT) a stated choice survey was administered to 463 households in Perth. After data cleaning, a total of 440 complete responses were used for further analysis. In the experimental setting four 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 A1.

Twelve experiments were generated with a block of six experiments randomly assigned to each respondent. The respondents were given the possibility to choose to complete either a paper-and-pencil questionnaire or a website questionnaire. Given the layout of the survey website (Surveymonkey, 2011), scenario randomisation was not possible; for this reason two separate set of experiments were generated and each respondent was presented with six experiments.

The respondents' choices indicated a high degree of non-trading and the following analysis investigates a possible cause for the non-trading behaviour of those who selected EV only. A joint Best-Worst choice model was proposed to overcome some of the challenges presented by non-trading behaviour in choice experiments.

4.1.1 Attitudes, Subjective norms and stated intention

As indicated, the questionnaire included 30 items measuring four attitudinal scales: Environmental concerns (EC), Subjective norms (SN), Excitement for new technologies (ENT), and Perceived usefulness (PU). Confirmatory factor analysis (CFA) was undertaken to calculate the latent factor scores for these four attitudinal constructs. Appendix A2 presents the items used to reflect the four latent constructs, along with the CFA results.

Excluding non-traders for other reasons (e.g., preference for current internal combustion engine cars, ICE, inertia effect, price sensitive respondents), there is a significant difference between the environmental concerns and subjective norms of EV non-traders and the traders (Table 1).

4.2 Non-traders

To better understand the behaviour of traders and non-traders in this sample, their profiles were compared based on their socio-demographics and attitudes, as given in Table 1. It indicates number of respondents along with their age, gender, education, willingness-to-spend (WTSpend) for next car, income, whether they would buy a new/used car, when do they intend to change their car, willingness to (WT) accept EV, and attitudes (Likert scales 1 to 5).

Socio-demographics were not significantly different between the two groups, although the EV non-traders Best seem to be younger, with higher education, and include more males. In contrast, EV non-traders Worst are older and earn about 20k more than the rest of the sample.

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).

Also, 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. Not surprisingly, 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 and Perceived usefulness of the EV technology. Keeping in mind the lowest sample of EV non-traders Worst and its impact on the statistical results, it appears that different motivations and decision mechanisms are influencing the choice for EV technologies.

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	Significance level P
AGE (years)	Av.	50.47	46.85	52.50	50.07	
	Stdev.	14.04	14.21	9.83	14.01	0.136
Household income ($000s)*	Av.	113.51	112.13	137.38	113.83	
	Stdev.	65.71	65.39	72.42	65.57	0.070
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	
	Stdev.	0.91	0.66	0.45	0.84	0.515
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	
	Stdev.	9.18	14.11	18.17	14.74	0.005
Likelihood to buy EV***	Av.	2.70	**3.77**	*1.50*	2.76	
	Stdev.	1.28	1.06	0.88	1.31	0.000
When changing car	Av.	3.36	3.39	3.37	3.37	
	Stdev.	1.42	1.66	1.93	1.65	0.958
Without ICE***	Av.	2.87	**3.54**	*1.58*	2.85	
	Stdev.	1.56	1.25	1.06	1.53	0.000
Frequency using EV***	Av.	3.55	**4.15**	*2.5*	3.58	
	Stdev.	1.2	1.85	1.38	1.21	0.000
EC***	Av.	2.65	**2.85**	*2.21*	2.66	
	Stdev.	0.49	0.48	0.71	0.54	0.008
SN**	Av.	2.72	**3.40**	*2.35*	2.73	
	Stdev.	1.22	1.52	1.42	1.28	0.013
ENT	Av.	3.54	3.75	3.20	3.55	
	Stdev.	0.91	0.95	1.08	0.92	0.724
PU	Av.	3.70	3.79	3.29	3.71	
	Stdev.	0.79	0.88	0.99	0.80	0.218
N		344	48	24	416	

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

4.2.1 Other Best and Worst Non-trading Findings

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 alternative. Perhaps these respondents used a predetermined ranking which was unaffected by the attribute levels. They seem to face the decision of purchasing a new car 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 high degree of distrust for alternative drive technologies. With other respondents it is not always clear why they chose to complete the survey and make the effort to return their responses by mail. The possible explanation is that there was a reward on offer for completed surveys and non-trading may be a strategy for completing the task quickly and without much thought.

When forecasting demand, the composite of the aggregate probabilities (expected share using sample enumeration) and the proportion of individuals who choose the alternative should be considered. In an experimental choice setting, it is not clear what the motivation for non-trading is. The respondent may clearly be a non-trader, or, alternatively, the respondents may be disengaged with the task and use non-trading as method to hasten their responses. 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.
Related to this, the responses may be affected by the cognitive burden and time required to analyse the experimental designs. This may explain differences between the online and pencil-and-paper responses for the non-trading behaviour displayed in both Best and Worst choices. 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 has substantial policy implications.

Finally, a respondent may use 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 always exhibit extreme preferences.

5. Determinants of Electric Vehicle Stated Choice

5.1 Investigating the role of Subjective Norms and Environmental Concerns in the Choice of EV (Best Only Data)

The choice model for the SC panel is estimated using a random effects component. 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. An error component is introduced to capture the correlations between Hybrid (HYB) and Electric Vehicles (EV) due to different refuelling technologies and relative novelty on the market. Similarly an error component is introduced to capture any correlations between Diesel (DIESEL) and Petrol (PET). 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 random effect choice model was run for a sample that included the 48 EV non-traders and another for the identified traders (Best). This method 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 concern for environment EC is significantly different over the two samples (P-value = 0.050), but the evidence about subjective norms SN is less clear (P-value= 0.105). The parameter estimate for the interaction between gender and the diesel ASC is significantly different when the estimation sample is for traders only (P-value <0.05).

Two choice models of the respondents' least preferred alternatives are listed on the right hand side of Table 2. The first model includes respondents that exhibited trading behaviour when selecting 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. 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.

Table 2: Choice Model Results for the Best and the Worst Data

Variable	Best Only Traders and EV Non-Traders N=399		Best Only Traders N=351		Worst Only Exhibiting trading choices or selecting EV only N=329		Worst Only Exhibiting trading choices N=305	
Random Effects	Par.	Asympt. Z value	Par.	Asymt. Z value	Par.	Asympt. Z value	Par.	Asympt. Z value
ASC EV	0.150	0.42	0.751	0.44	0.190	0.08	0.261	0.11
ASC PET	**0.579**	2.71	**0.531**	2.71	-0.366	1.97	-0.351	1.81
ASC Hyb	**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 PET***	**1.926**	12.79	**1.153**	7.14	**0.979**	9.04	**0.989**	8.74
ASC HYB***	**1.783**	10.38	**1.318**	8.14	**0.956**	4.18	**0.981**	4.14
Error Components								
EV and HYB	0.240	1.25	0.469	1.82	0.936	4.49	0.904	4.15
PET 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
RUNCST***	**-0.259**	9.08	**-0.253**	8.81	**-0.270**	5.69	**-0.246**	4.87
EV-RNG	**-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
CHRGTIME***	**-0.004**	5.64	**-0.004**	5.62	**-0.008**	4.7	**-0.008**	4.72
BATCAP	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
ENGSIZE	**1.386**	6.66	**1.273**	5.98	0.444	1.26	0.261	0.72
Interactions								
EENV**	**1.220**	4.58	**0.730**	3.04	-0.091	0.25	-0.193	0.55
ESN	**0.406**	5.18	**0.280**	3.18	-0.008	0.05	-0.011	0.07
ENVGHG	-0.018	0.95	-0.023	1.15	**-0.120**	5.32	**-0.106**	4.00
MALED	**1.386**	5.55	**0.651**	4.41	0.026	0.17	-0.057	0.36
Model Statistics								
LL Model	-2,759.92		-2,469.08		2,851.61		2,610.39	
LL ASC's	-3,751.31		-2,994.39		1,944.26		1,797.82	
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 (values greater than 1.65 mean parameter is significant at the 10% level of confidence; Z >1.96 indicates sig. at the 5% level and Z>2.35, or ***, sig. at the 1% level of confidence, across all models).

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 disregard 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 most and least preferred 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.

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 as outlined in Section 4 was also adopted here. However, because of the two sources of data (Best and Worst) a preliminary nested logit is used to estimate a scale parameter. The scale parameter of 1.752 was used to rescale the Worst data. Most of the attributes of the vehicles are estimated jointly using the best and the rescaled worst data, except engine size (ENGSIZE) 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 (RUNCST). However, the impact of driving range on the choice of the electric vehicle (EV-RNG) has an unexpected sign. Larger engines (non-ev alternatives - ENGSIZE) are attractive as are less noisy (NOISE) vehicles. Despite removing the non-traders from the estimation sample, higher subjective norm scales are still associated with the choice of EV (Best). 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.

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.

Table 3: A Joint B-W Random Effects and Error Component Choice Model in the Presence of Non-traders

Variable	Best choice data N= 294 Traders Best and Worst N= 61 Traders Best only		Worst choice data N= 294 Traders Best and Worst N= 39 Traders Worst only	
Random Effects	Par	Asympt. Z value	Par	Asympt. Z value
ASC EV	1.530	0.97	-2.008	2.44
ASC PET	**0.597**	3.10	**-0.419**	3.53
ASC Hyb	**2.605**	5.83	**-1.565**	5.96
St. Dev. of Random effects				
ASC EV***	**1.111**	6.95	**1.967**	8.24
ASC PET***	**1.128**	7.12	**1.087**	9.67
ASC HYB***	**1.235**	7.65	**1.060**	4.60
Error Components				
EV and HYB	**1.062**	6.24	0.279	1.11
PET and DIESEL	0.205	0.49	**0.796**	3.43
ATTRIBUTES SC	Jointly estimated parameters for the attributes presented in the best and worst stated choice experiment. Scale parameter for worst =1.72 Par		Asympt. Z	
PRICE***	**-0.068**		10.42	
RUNCST***	**-0.267**		11.21	
EV-RNG***	**-0.011**		3.22	
GHG***	**0.100**		2.42	
NOISE***	**-0.394**		8.23	
CHRGTIME***	**-0.005**		7.07	
BATCAP	-0.233		0.15	
RNG	0.001		1.33	
ENGSIZE (best only)***	**1.155**		6.72	
Interactions				
ENV*EV ASC	0.355	1.48	-	-
SN*EV ASC	**0.298**	3.35	-	-
ENV*GHG	**-0.039**	2.43	**-0.065**	4.18
MALE*Diesel ASC	**0.613**	3.73	-	-
Model Statistics				
LL Model	-8,818.91			
LL ASC's	-4,376.03			
McFadden's pseudo r^2	0.504			
AIC/N	2.078			

Note: Par. = parameter estimate; Asympt. = asymptotic Z value (values greater than 1.65 mean parameter is significant at the 10% level of confidence; Z >1.96 indicates sig. at the 5% level and Z>2.35, or ***, sig. at the 1% level of confidence, for both models.

6. Conclusion

The paper examines possible response bias as being the cause of non-trading in a stated choice survey. When collected stated choice data as part of the Western Australian Electric Vehicle Trial (WAEVT) a high degree of non-trading was identified. The analysis given in this paper concentrates on the respondents who selected electric vehicles only. It was found that these respondents indicated significantly different environmental concerns and subjective norms in the context of electric vehicle ownership. The EV non-traders Best scored higher, whereas the EV non-traders Worst displayed lower scores on the latent construct scales, compared to the traders. Two response biases were suggested as being influential. Social desirability was thought to be identified with a higher score on being concerned with the environment; worrying about how others viewed their behaviour (SN) and stated intentions (both the direct pre-experiment questions on intention to purchase and use an electric vehicle and the responses to the stated choice scenarios) were assessed as being a reflection of the demand effect. An examination of the data showed that non-traders differed from the remaining respondents significantly across these three dimensions.

At the time of examining these data it was also noted that two of the three components of the questionnaire were direct questions about EV and the response bias may have been related to demand characteristics (or when the respondents alters their behaviour because that is what they think the experiment is asking them to do so). Whist, altering behaviour within an experiment may not be an analogue to ‘second guessing’, the purpose of an experiment in psychology – there may be a degree of influence on behaviour due to the context of the questionnaire.

The choice results were inconclusive on the actual cause of the non-trading, but the associations between stated behaviour and EC along with SN 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 SN or hold lower than average EC were not *on average* selecting the electric vehicles as the Worst option. A joint Best-Worst choice model was estimated. The results indicated that SN are associated with the selection of an electric vehicle (Best), but EC were associated with the environmental performance of the vehicles rather than just the label.

Regardless of the respondents’ motivations, this research shows that more attention needs to be paid to selectivity and response bias and survey design. Mail-out surveys seem to attract a bias sample of an *interested* segment of the community. It is suggested that different survey mechanisms may be more appropriate when the context is somewhat emotive. This survey was followed up by a secondary online panel and the results of these data will be published elsewhere.

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. Comparisons with more mature EV markets, such as Norway, suggest while early adopters are more likely to be younger males, with higher education and income, with a larger family, living in urban areas, these differences may wane over time (Figenbaum *et al.*, 2014). Similarly, there appears to be greater acceptance of EVs as not simply a second car, but a replacement for the primary vehicle as the technology diffuses through society. Australia is some way behind this scenario, but it is not unreasonable to suggest that as the technology matures, familiarity/acceptance grows and the relative costs come down compared to ICE vehicles, that we may witness greater uptake of EVs in the next 5-10 years.

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GLOSSARY OF ACRONYMS

ASC: Alternative specific constant

B-W: Best-Worst

BATCAP: The life of the battery

CHRGTIME: The time taken to recharge an EV or plug in hybrid vehicle

DIESEL: Diesel filled vehicle

EC: Environmental concerns

ENT: Excitement for new technologies

EV: Electric Vehicle

EV-RNG: The range of the EV

GHG: The greenhouse gas emission level of the vehicle

HYB: Plug in Hybrid EV

MNL: Multinomial Logit Model

NOISE: An indicator of the noise level of the vehicle

PET: Petrol fuelled vehicle

PRICE: Purchase Price of the vehicle

PU: Perceived usefulness

RNG: The range of vehicles other than EV

RUNCST: The running cost expressed in dollars per 100km

SN: Subjective norms

SC: Stated Choice

TPB: Theory of Planned Behaviour

TAM: Technology Acceptance Model

ICE: Internal Combustion Engine

Appendix A1: 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 minutes of home-charging)
	Petrol	3	600; 700; 800
	Diesel	3	800; 900; 1000
Running cost ($/100km)	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
Green House Gas emissions (kg/100km)	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 charging stations	EV	3	500; 1000; 1500
	Plug-In Hybrid	N/A	Charging at home
	Petrol/ Diesel	N/A	N/A

Appendix A2: 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		
	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		