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Asymmetrical Preference
Formation in Willingness to
Pay Estimates in Discrete
Choice Models

By

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ABSTRACT: Individuals when faced with choices amongst a number of alternatives often adopt a variety of processing rules, ranging from simple linear to complex non-linear treatment of each attribute defining the offer of each alternative. In recent years, there has been a growing interest in the choice process as a basis of understanding how best to represent attributes in choice outcome models. In this paper, in the context of choice amongst tolled and non-tolled routes, we investigate the presence of asymmetry in preferences, drawing on ideas from prospect theory to test for framing effects and differential willingness to pay according to whether we are valuing gains or losses. The findings offer clear evidence of an asymmetrical response to increases and decreases in attributes when compared to the corresponding values for a reference alternative. The degree of asymmetry varies across attributes and population segments, but crucially is independent of the inclusion or otherwise of an additional constant for the reference alternative, contrary to earlier findings.

KEY WORDS: *Preference asymmetry, valuation of travel time savings, pivot designs*

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1. Introduction

The computation of willingness to pay (WTP) indicators is one of the main objectives of studies making use of random utility models (RUM) belonging to the family of discrete choice models. WTP measures give an indication of the readiness of decision makers to accept an increase in cost in return for a gain in attractiveness of an alternative along some other dimension, such as travel time or headway.

The case of travel time is of particular interest. Indeed, estimates of the valuation of travel time savings (VTTS), giving the implied willingness by travellers to accept increases in travel cost in return for decreases in travel time, are of crucial interest to policy makers, such as in cost benefit analyses (CBA) for proposed new infrastructure. Given this importance of VTTS measures in transport planning, it should come as no surprise that there is an ever increasing body of research looking at ways of increasing the accuracy of VTTS estimates.

Aside from discussing the impact of model specification (e.g., Gaudry *et al.*, 1989) and survey design (e.g., Hensher, 2004b) on VTTS estimates, much of the recent literature has focussed on the representation of the (random) variations in behaviour across respondents (see for example, Algiers *et al.*, 1998, Hensher and Greene, 2003, Fosgerau, 2005 and Hess *et al.*, 2005). The findings from these various papers have shown the benefit of accounting for variations in tastes (and hence also VTTS) across respondents, in terms of better model performance, but also through a reduction in the risk of bias. Additionally, this work has however highlighted the important issues of specification that need to be faced when allowing for random taste heterogeneity. Another issue that has repeatedly been addressed is the relationship between the VTTS and attributes of the respondents, such as income, where Axhausen *et al.* (2006) for example show the benefit of approaches allowing for a continuous impact of income and trip distance on the VTTS.

The vast majority of studies aimed at producing VTTS measures make use of data collected in Stated Preference (SP) surveys, in which respondents are asked to state their preference amongst a number of hypothetical alternatives described by a set of attributes. While there are differences between surveys in terms of context (e.g., mode choice, route choice, etc.) and design (e.g., number of alternatives, attributes, etc.), the basic objective is the same, with the studies aiming to provide estimates of the relative sensitivities to changes in travel time and travel cost.

By looking at existing work in the area of VTTS studies, an interesting pattern emerges. Indeed, while the representation of inter-agent taste heterogeneity and the relationship between respondents' socio-demographic attributes and their WTP measures, such as VTTS, has been the topic of an ever increasing number of studies, comparatively little effort has gone into analysing how respondents process the attributes describing the various alternatives in SP surveys. However, there are potentially significant differences across respondents in their attribute processing strategies (APS), and not accounting for these differences can lead to biased WTP estimates, as highlighted in a recent study by Hensher (2006). The results of the study by Hensher show not only that by accounting for the fact that some individuals consistently ignore certain attributes or sum up individual components of travel cost and travel time, different VTTS estimates are obtained, but also indicate that this leads to a reduction in the scope for retrieving

random taste heterogeneity. This shows that by accounting for APS, modellers can reduce the impact of the unobserved part of utility on model results.

In this paper, we look at a different issue that falls within the general field of attribute processing strategies, namely whether there are asymmetries in response to increases and decreases in attribute levels of SP alternatives in the presence of a reference alternative¹. As such, in contrast to estimating a single parameter for each attribute as is normally the case in SP studies (including those incorporating reference alternatives), we estimate models that incorporate different parameters associated with attribute levels that are either higher or lower than the base reference alternative level. This approach allows us to test whether respondents' preferences for an attribute are different depending on whether an attribute is either framed negatively or positively around the reference or neutral point.

The use of a framing approach relates the work described in this paper to the notion of prospect theory introduced by Kahneman and Tversky (1979), according to which, due to limitations on their ability to cognitively solve difficult problems, decision makers simplify the choice process by evaluating the gains or losses to be made by choosing a specific alternative, relative to a neutral or status quo point. That is, decision makers adopt a constant level for some psychological construct and define this as the neutral point of reference. It is from this point of reference that their basis of comparison of competing choices is made (Hastie and Dawes 2001).

Several researchers have confirmed the existence of such framing effects in decision making processes. For example, Payne *et al.* (1988), showed that respondents change their decision behaviour depending upon the level of correlation amongst the attributes of experiments (i.e., how different attributes are from each other). Mazzota and Opaluch (1995) showed that variations in the degree to which attribute levels vary across alternatives result in significantly different parameter estimates whilst Swait and Adamowicz (1996) show that the difference between alternatives in attribute space significantly influence choice behaviour. The results of DeShazo and Fermo (2002) and Hensher (in press) also confirm these findings.

The use of the above described framing approach is made possible through the use of SP design strategies that relate the experiences of sampled respondents to the experiment (see for example, Hensher 2004a, in press, Hensher *et al.* 2005; Train and Wilson 2006). The use of a respondent's experiences or knowledge base to derive the attribute levels of the experiment recognises not only the framing effects of prospect theory but also encapsulates a broader range of psychological and economic theories, such as case-based decisions theory and minimum-regret theory (see Starmer 2000; Hensher 2004a; Kahnemann and Tversky 1979; Gilboa *et al.* 2002). Starmer (2000, p 353) in particular is a strong advocate for the use of reference points (e.g., a current trip) in decision theory:

“While some economists might be tempted to think that questions about how reference points are determined sound more like psychological than economic issues, recent research is showing that understanding the role of reference points may be an important step in explaining real economic behaviour in the field”

¹ While, like the majority of the above discussion, the work described in this paper centres on the estimation of VTTS measures, the findings extend to other WTP measures, as well as independent marginal utility coefficients.

The use of respondents' experiences (called reference alternatives) in SP experiments acts to frame the decision context of the choice task within some existing memory schema of the individual respondents and hence makes preference-revelation more meaningful at the level of the individual, consistent with prospect theory. The possible existence of framing effects, of which reference dependence is a popular interpretation, provides adaptive support in trading off the desire to make a good choice against the cognitive effort involved in processing the information provided in SP tasks.

The incorporation of reference alternatives into SP tasks (which we term pivot designs as the SP alternatives are designed as percentages or pivots around the reference alternative) is one thing. How to handle the econometric modelling of such data is another. Train and Wilson (2006) show that reference based SP experiments may induce endogeneity in the attributes of the SP alternatives, but are able to account for this through the use of mixed logit models. In this paper, we are not so much concerned with issues of endogeneity, but rather with the issue of framing effects which prospect theory suggests should exist within such data. Depending on the percentages assumed in generating pivot designs, it is possible that over the course of an experiment, the attribute levels of the SP alternatives may be either greater than or less than the level of the respondent's reference alternative. For example, if the travel time in the reference alternative is 20 minutes, the attribute levels shown for the SP alternatives might be 15 (-25 percent), 20 (zero percent change) and 25 (+25 percent) minutes. In such cases, prospect theory would suggest that the marginal (dis)utility for attributes may be very different when framed positively relative to a reference alternative (i.e., a value of 15), than when framed negatively (i.e., a value of 25). This framing effect also has implications on the willingness to pay estimates generated from such studies.

As highlighted above, and as detailed in Section 3, the modelling approach used in this paper contrasts with that used typically in discrete choice analyses. As such, existing studies generally use a standard expected utility theory approach, in which the utility of an alternative is a function of the tastes of the respondents and the absolute attributes of the alternative. This applies to discrete choice analyses in general, and VTTS studies by extension. While the work described in this paper thus presents a departure from the status quo in VTTS analyses, it should be noted that this applies primarily to the *published* state of practice. Indeed, it must be acknowledged that several existing VTTS studies have allowed for an asymmetrical response to gains and losses in travel time and travel cost. These approaches have notably been used in a number of national value of time studies in Europe, such as in the Netherlands (HCG, 1990) and in the United Kingdom (AMR&HCG, 1999, Bates and Whelan, 2001). However, the results of these studies have generally only been discussed in consulting reports and government documents, with one of the few published accounts of such studies being the summary by Gunn (2001)². The fact that the overwhelming majority of studies still rely on a symmetrical modelling approach is an indication of the lack of dissemination of such material.

From the above discussion, it can be seen that, even though this paper does not per se present any major theoretical innovations, it serves the purpose of bringing this issue of asymmetrical preference structures to the (renewed) attention of a wider audience, with the hope of affecting the state of practice. Additionally, however, the work does differ somewhat from previous efforts accounting for differences in the response to gains and

² Other discussions are given in unpublished and difficult to obtain conference proceedings, such as Burge *et al.* (2004), and Van de Kaa (2005)

losses. Indeed, existing work has seemingly always been based on a simplistic binomial survey design making use of two variables only, travel time and travel cost, with one alternative being cheaper while the other is faster. The data used in the analysis discussed in this paper uses two separate travel time components (free flow and slowed down) as well as two separate travel cost components (running cost and tolls). This makes the analysis far more general, not only by allowing for an asymmetrical treatment of a greater number of parameters, but also by moving away from a simple money/time trade-off situation³. Furthermore, each choice situation used in the current data includes a reference alternative corresponding to an observed trip, meaning that the actual *reference point* used in the modelling analysis is always presented to respondents. Again, this was seemingly not the case in the studies cited above; here the design was such that the reference values for the cost and time attributes were used in some but not all of the choice situations, and not necessarily in conjunction (i.e., within the same alternative).

Before proceeding to the description of our study, one final point deserves to be mentioned. In previous studies (cf., Bates and Whelan, 2001), it has been observed that with the inclusion of an *inertia* term, which was essentially just a constant associated with the current (reference) alternative, the asymmetries in response largely disappear. One of the aims of the present analysis is to see whether this finding holds with the data used here. In this context, it should be noted that an important difference arises between the current and previous studies.

The remainder of the paper is structured as follows. In Section 2, we describe the data setting and survey method including the design of the SP experiment. Section 3 details the utility specifications of the estimated models, with the modelling results presented in Section 4. Conclusions and general discussion are given in Section 5.

2. Data

The data are drawn from a study undertaken in Sydney in 2004, in the context of car driving commuters and non-commuters making choices from a range of levels of service packages defined in terms of travel times and costs, including a toll where applicable.

To ensure that we captured a large number of travel circumstances, enabling us to see how individuals trade off different levels of travel times with various levels of tolls, we sampled individuals who had recently undertaken trips of various travel times (called trip length segmentation), in locations where toll roads currently exist. To ensure some variety in trip length, three segments were investigated: no more than 30 minutes, 31 to 60 minutes, and more than 61 minutes (capped at two hours).

A telephone call was used to establish eligible participants from households stratified geographically, and a time and location was agreed for a face-to-face computer aided personal interview (CAPI). The actual SP questionnaire presented respondents with sixteen choice situations, each giving a choice between their current route and two alternative routes with varying trip attributes. A D-efficient design was used in the generation of the SP questionnaires (see for example, Bliemer *et al.*, 2005; Burgess and Street, 2003; Carlsson and Martinsson, 2003; Ferrini and Scarpa 2006; Huber and

³ This is further enhanced by the use of three rather than two alternatives.

Zwerina, 1996; Kanninen, 2002; Kessels *et al.*, 2006; Kuhfeld *et al.*, 1994; Lazari and Anderson, 1994; Sándor and Wedel, 2001, 2002, 2005; Street and Burgess, 2004; Street *et al.*, 2001).

The two SP alternatives are unlabelled routes. The trip attributes associated with each route are free flow time, slowed down time, trip travel time variability, vehicle running cost (essentially fuel) and the toll cost. These were identified from reviews of the literature and supported by the effectiveness of previous VTS studies undertaken by Hensher (2001). In addition, previous studies were used to establishing the priors (i.e., parameter estimates associated with each attribute) for designing the experiment. All attributes of the SP alternatives are based on the values of the current trip. Variability in travel time for the current alternative was calculated as the difference between the longest and shortest trip time provided in non-SP questions. The SP alternative values for this attribute are variations around the total trip time. For all other attributes, the values for the SP alternatives are variations around the values for the current trip. The variations used for each attribute are given in Table 1.

Table 1: Profile of attribute ranges in the SP design

	Free-flow time	Slowed down time	Variability	Running costs	Toll costs
Level 1	- 50%	- 50%	+ 5%	- 50%	- 100%
Level 2	- 20%	- 20%	+ 10%	- 20%	+ 20%
Level 3	+ 10%	+ 10%	+ 15%	+ 10%	+ 40%
Level 4	+ 40%	+ 40%	+ 20%	+ 40%	+ 60%

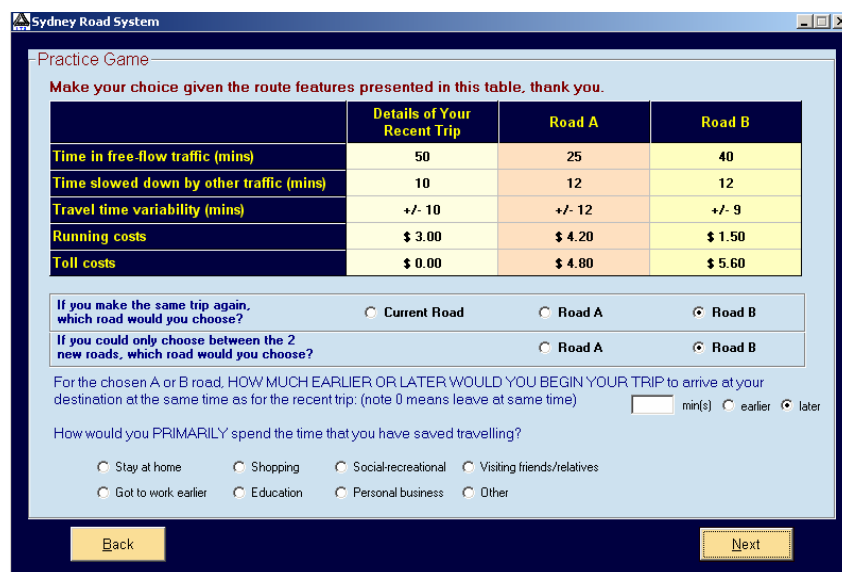


Figure 1: An example of a stated choice screen

The experimental design has three versions (one for each trip segment) of 16 choice sets (games). The design has no dominance given the assumption that less of all attributes is better. The distinction between free flow and slowed down time is designed to promote the differences in the quality of travel time between various routes – especially a tolled route and a non-tolled route, and is separate to the influence of total time. Free flow time is interpreted with reference to a trip at 3am when there are no delays due to

traffic.⁴ An example of a stated choice screen, for the current trip (or reference) alternative and two design-generated combinations of actual attribute levels (based on a percentage variation from the reference alternative obtained from Table 1) is shown in Figure 1.

The sample of 467 effective interviews (243 commuters and 224 non-commuters), with each person responding to 16 choice sets, resulted in 3,888 commuter and 3,584 non-commuter observations for model estimation. Data cleaning was performed, with respondents observed to always choose the reference alternative across their 16 choice situations being removed from the analysis. This resulted in a final estimation sample containing 3,792 observations from 237 respondents in the commuter segment, and 3,280 observations from 205 respondents in the non-commuter segment.

3. Description of approach

In the analysis presented in this paper, only four of the five attributes used in the SP design were used in the analysis, where trip time variability over repeated trips was excluded⁵.

3.1. Symmetrical modelling approach

In a purely linear model, the utility of alternative i is then be given by:

$$U_i = \delta_i + \delta_{T(i)} + \delta_{FC(i)} + \beta_{FF} \cdot FF_i + \beta_{SDT} \cdot SDT_i + \beta_C \cdot C_i + \beta_T \cdot T_i \quad (1)$$

where δ_i is a constant associated with alternative i (normalised to zero for the third alternative⁶), and β_{FF} , β_{SDT} , β_C and β_T are the coefficients (to be estimated) that are associated with free flow travel time (FF), slowed-down travel time (SDT), running cost (C), and road tolls (T) respectively, for alternative i . Travel time attributes are expressed in minutes, while travel cost attributes are expressed in AUD. The two additional parameters $\delta_{T(i)}$ and $\delta_{FC(i)}$ are only estimated in the case where a toll is charged for alternative i and in the case where alternative i includes no free flow time (i.e., fully congested).

⁴ This distinction does not imply that there is a specific minute of a trip that is free flow per se but it does tell respondents that there is a certain amount of the total time that is slowed down due to traffic, and hence that a balance is not slowed down (i.e., is free flow, like one observes typically at 3am).

⁵ This was motivated primarily by the high percentage of respondents stating that they consistently ignored trip time variability in completing the SP questionnaires, and the resulting low levels of statistical significance for the trip time variability parameter for the remainder of the population.

⁶ The significance of an ASC related to an unlabelled alternative simply implies that after controlling for the effects of the modelled attributes, this alternative has been chosen more or less frequently than the base alternative. It is possible that this might be the case because the alternative is close to the reference alternative, or that culturally, those undertaking the experiment tend to read left to right. Failure to estimate an ASC would in this case correlate the alternative order effect into the other estimated parameters, possibly distorting the model results.

3.2. Basic asymmetrical approach

The above specification can be easily adapted to work with differences in relation to a reference alternative, as opposed to using the absolute values presented to respondents in the SP experiments. In the present context, the most obvious choice for such a reference alternative is the *current* alternative, hereafter referred to as the RP (revealed preference) alternative. The utility functions for the various alternatives can then be adapted as follows.

For the reference alternative r , the utility function is now rewritten so as to include only the three dummy variables δ_r (ASC), $\delta_{T(r)}$ (toll road dummy) and $\delta_{FC(r)}$ (fully congested dummy). For SP alternative j (where $j \neq r$), the utility function is now given by:

$$U_{j,new} = \delta_j + \delta_{T(j)} + \delta_{FC(j)} + \beta_{FF} \cdot (FF_j - FF_r) + \beta_{SDT} \cdot (SDT_j - SDT_r) + \beta_C \cdot (C_j - C_r) + \beta_T \cdot (T_j - T_r) \quad (2)$$

It can easily be seen that the adapted model is equivalent to the old model, given that all utilities are changed in the same fashion, namely by taking:

$$U_{j,new} = U_j - \beta_{FF} \cdot FF_r - \beta_{SDT} \cdot SDT_r - \beta_C \cdot C_r - \beta_T \cdot T_r \quad (3)$$

As such, up to this point, there is no reason for using the adapted approach and hence a further transformation is required. In the new formulation, the utility function for alternative j is now represented as:

$$U_{j,new} = \delta_j + \delta_{T(j)} + \delta_{FC(j)} + \beta_{FF(inc)} \cdot \max(FF_j - FF_r, 0) + \beta_{FF(dec)} \cdot \max(FF_r - FF_j, 0) + \beta_{SDT(inc)} \cdot \max(SDT_j - SDT_r, 0) + \beta_{SDT(dec)} \cdot \max(SDT_r - SDT_j, 0) + \beta_{C(inc)} \cdot \max(C_j - C_r, 0) + \beta_{C(dec)} \cdot \max(C_r - C_j, 0) + \beta_{T(inc)} \cdot \max(T_j - T_r, 0) + \beta_{T(dec)} \cdot \max(T_r - T_j, 0) \quad (4)$$

With this specification, separate coefficients are estimated for increases and decreases in an attribute in relation to the reference alternative, hence allowing for asymmetrical responses.

3.3. Asymmetrical approach with differential response for increases from zero

To further increase the flexibility of the specification, a final change to the utility function is performed, recognising that respondents might react differently to changes in an attribute for which the value in the reference alternative was equal to zero. This applies only for increases in free flow travel time, slowed down time and road tolls, as the reference alternative always has a non-zero cost attribute. The utility function is now rewritten as:

$$U_{j,new} = \delta_j + \delta_{T(j)} + \delta_{FC(j)} + \beta_{FF(inc)} \cdot \max(FF_j - FF_r, 0) + \beta_{FF(inc,zero)} \cdot FF_j \cdot I(FF_r = 0) + \beta_{FF(dec)} \cdot \max(FF_r - FF_j, 0) + \beta_{SDT(inc)} \cdot \max(SDT_j - SDT_r, 0) + \beta_{SDT(inc,zero)} \cdot SDT_j \cdot I(SDT_r = 0) + \beta_{SDT(dec)} \cdot \max(SDT_r - SDT_j, 0)$$

$$\begin{aligned}
& + \beta_{C(\text{inc})} \cdot \max(C_j - C_r, 0) + \beta_{C(\text{dec})} \cdot \max(C_r - C_j, 0) + \beta_{T(\text{inc})} \cdot \max(T_j - T_r, 0) \\
& + \beta_{T(\text{inc}, \text{zero})} \cdot T_j \cdot I(T_r = 0) + \beta_{T(\text{dec})} \cdot \max(T_r - T_j, 0)
\end{aligned} \tag{5}$$

where, as an example, $I(\text{FF}_r = 0)$ is equal to one only if the free flow time for the reference alternative is equal to zero. From the above, it can be seen that $\beta_{\text{FF}(\text{inc})}$ will be estimated for all increases, including those from zero, while the additional coefficient $\beta_{\text{FF}(\text{inc}, \text{zero})}$ is only estimated for increases from zero. As such, $\beta_{\text{FF}(\text{inc}, \text{zero})}$ represents a bonus that needs to be added to $\beta_{\text{FF}(\text{inc})}$ when FF_r is zero. With a negative value for $\beta_{\text{FF}(\text{inc}, \text{zero})}$ (in addition to a negative value for $\beta_{\text{FF}(\text{inc})}$), increases in free flow time from zero will be valued more negatively than increases from a non-zero value, with the converse applying in the case of positive estimates for $\beta_{\text{FF}(\text{inc}, \text{zero})}$. The same reasoning applies for $\beta_{\text{SDT}(\text{inc}, \text{zero})}$ and $\beta_{T(\text{inc}, \text{zero})}$.

3.4. Recognising the repeated choice nature of the dataset

A point that deserves some attention before describing the results of the modelling analysis is the way in which the models deal with the repeated choice nature of the data. In the case of a dataset with sixteen observations per individual, it should be recognised that there are potentially significant levels of correlation between the behaviour of respondent n in choice situation t_i and choice situation t_j , with $i \neq j$. Not accounting for this correlation can potentially have significant effects on model results, especially in terms of biased standard errors (cf., Ortúzar and Willumsen, 2001). In an analysis looking at differences between the response to gains and losses, issues with over- or underestimated standard errors can clearly lead to misleading conclusions.

Rather than relying on the use of a lagged response formulation (cf., Train, 2003) or a jackknife correction approach (cf., Cirillo *et al.*, 2000), we make use of an error components specification of the mixed logit (MMNL) model. This differs from the nowadays commonly used approach of capturing the serial correlation with the help of a random coefficients formulation in which the tastes are assumed to vary across respondents but stay constant across observations for the same respondent. This approach not only makes the considerable assumption of an absence of inter-observational variation, but the results are potentially also affected by confounding between serial correlation and random taste heterogeneity. In this paper, we aim to specify the models so that the error components capture individual specific correlation. For reasons of identification, it is clearly not possible to add the same error component to each of the utility functions. However, adding the error component to all but one of the utility functions not only leads to a question as to what normalisation to use, but also leads to an approximation of a nested logit (NL) model and introduces heteroscedasticity (cf., Walker, 2001).

Our approach is slightly different⁷. With $V_{\text{RP}, \text{base}}$, $V_{\text{SP1}, \text{base}}$, and $V_{\text{SP2}, \text{base}}$ giving the base utilities for the three alternatives⁸, the final utility function is given by

$$\begin{aligned}
U_{\text{RP}} &= V_{\text{RP}, \text{base}} + \sigma \xi_{\text{RP}} + \varepsilon_{\text{RP}} \\
U_{\text{SP}, 1} &= V_{\text{SP1}, \text{base}} + \sigma \xi_{\text{SP1}} + \varepsilon_{\text{SP1}} \\
U_{\text{SP}, 2} &= V_{\text{SP2}, \text{base}} + \sigma \xi_{\text{SP2}} + \varepsilon_{\text{SP2}}
\end{aligned} \tag{6}$$

⁷ We thank Andrew Daly for this suggestion.

⁸ Independently of which specification is used, i.e. models based on equation (1) or equation (5).

where ε_{RP} , ε_{SP1} , and ε_{SP2} are the usual IID type I extreme value terms and ξ_{RP} , ξ_{SP1} and ξ_{SP2} are three independently distributed Normal variates with a zero mean and a standard deviation of 1. To allow for correlation across replications for the same individual, the integration is carried out at the respondent level rather than the individual observation level. However, the fact that independent $N(0,1)$ draws are used for different alternatives means that the correlation does not extend to correlation across alternatives but is restricted to correlation across replications for the same individual and a given alternative. Finally, the fact that the separate error components are distributed identically means that the model remains homoscedastic. To allow us to give an account of the effect of using this formulation, the cross-sectional results are presented alongside the results using equation (6).

4. Model results

This section summarises the results of the modelling analysis. We first briefly look at the results for the base model, using the utility specification given in equation (1), before describing in more detail the results for the main model, using the utility specification given in equation (5), with the additional panel error components, as set out in equation (6).

In addition to respondents' choices, the dataset includes information on respondents' attribute processing strategies (APS), detailing whether respondents indicated that they systematically ignored certain attributes, as well as whether they processed the two individual cost and the two individual time components independently, or whether they summed them up (i.e., leading to a single cost component and a single time component). Efforts were made to take this information into account in the modelling analysis (cf., Hensher *et al.* 2005a and Rose *et al.* 2005). However, in the present analysis (across both population segments), satisfactory results were only obtained by accounting for the ignoring of travel cost and toll costs.

4.1. Base models

The results for the base models are shown in Table 2, where separate models were estimated for commuters and non-commuters, and where the cross-sectional results are shown alongside the panel ones.

Table 2: Estimation results for base models

	Non-commuters				Commuters			
	Panel		Cross-sectional		Panel		Cross-sectional	
	Coeff.	(<i>t</i> -ratio)	Coeff.	(<i>t</i> -ratio)	Coeff.	(<i>t</i> -ratio)	Coeff.	(<i>t</i> -ratio)
δ_{RP}	0.1957	(1.44)	0.1779	(2.38)	0.0692	(0.54)	0.1480	(2.28)
δ_{SP1}	0.1896	(2.74)	0.1527	(2.58)	0.1107	(1.62)	0.0843	(1.62)
β_C	-0.4129	(-9.21)	-0.3673	(-12.81)	-0.4119	(-11.60)	-0.3430	(-13.92)
β_T	-0.4381	(-4.18)	-0.4099	(-8.14)	-0.3435	(-5.30)	-0.2686	(-6.98)
β_{FF}	-0.0921	(-11.22)	-0.0815	(-17.76)	-0.0913	(-10.06)	-0.0749	(-16.65)
β_{SDT}	-0.1029	(-12.25)	-0.0928	(-17.16)	-0.1139	(-16.01)	-0.0954	(-26.07)
δ_{FC}	-2.0184	(-14.93)	-1.9460	(-2.07)	0.3916	(0.63)	0.0720	(0.31)
δ_T	-0.3068	(-0.77)	-0.1544	(-0.76)	-0.4712	(-1.92)	-0.5060	(-3.24)
σ	0.6655	(12.00)	-	-	0.9045	(16.25)	-	-
Sample	3280		3280		3792		3792	
Final LL	-2305.27		-2396.71		-2630.41		-2855.23	
Adj. ρ^2	0.3578		0.3327		0.3664		0.3127	

The results show that, in both (panel) models, the four main coefficients (β_{FF} , β_{SDT} , β_C and β_T) are all statistically significant and of the correct sign. The constant estimated for the RP alternative is positive in both models, but not significantly different from zero, while the constant for the first SP alternative is only significant at the 89 percent level for the commuter model. The dummy variable associated with toll roads is negative in both models, but is only significantly different from zero in the model for commuters. Finally, the dummy variable associated with fully congested alternatives is significant and negative for non-commuters, while it is positive and not significantly different from zero for commuters. The insignificant coefficients are retained in the models to facilitate comparison with the more advanced models estimated in the remainder of the analysis.

Before proceeding to a more detailed analysis of the results, it is of interest to briefly look at the impacts of the panel specification from equation (6). In both population segments, the inclusion of the error component leads to very significant gains in model fit, at the cost of one additional parameter (σ). As expected, the actual parameter estimates remain largely unaffected (cf., Ortúzar and Willumsen, 2001), with the exception of those that were poorly estimated (high standard errors) in the first place. The real differences however arise in the standard errors associated with the estimated parameters. For the vast majority of parameters, there is an upward correction of the standard errors, which is consistent with many previous results using other approaches. However, for the fully congested dummy variable in the non-commuter model, the standard error decreases dramatically, leading to a seven-fold increase in the asymptotic *t*-ratio. This confirms results by Ortúzar *et al.* (2000) who, in an application using a jackknife approach, observed that the changes in the standard errors are not necessarily one-directional.

With the differences between the panel and cross-sectional approaches being restricted primarily to the standard errors, the discussion of the results in the remainder of this section focuses exclusively on the models using the specification from equation (6).

It is of interest to briefly look into the differences in response to the separate travel cost and travel time components. For this, standard errors were calculated for the differences between β_C and β_T , as well as between β_{FF} and β_{SDT} . The associated asymptotic t -ratios are shown in Table 3.

Table 3: Asymptotic t -ratios for differences between separate travel time and travel cost coefficients

	Non-commuters	Commuters
β_C vs β_T	0.2351	1.0222
β_{FF} vs β_{SDT}	1.0406	2.3208

The results show that the difference between the two cost coefficients (travel cost and road toll) is not significant at the usual 95 percent level in either segment (with levels of 19 percent and 69 percent for non-commuters and commuters respectively). The difference between the two travel time components (free flow and slowed down) is significant at the 70 percent level for non-commuters, while it is highly significant in the case of commuters⁹.

In the present context, it is also worth looking at the difference in sensitivity to the two travel time and travel cost coefficients, where the results from Table 3 again need to be borne in mind. A simple calculation on the basis of the estimates from Table 2 shows that in both segments, the marginal disutility of slowed down time is greater than the marginal disutility of free flow time, where the difference is greater for commuters than for non-commuters. On the other hand, while road tolls have a higher marginal disutility than running cost for non-commuters, the converse is the case for commuters, where the associated negative and significant estimate for δ_T in the commuter segments however needs to be borne in mind. These ratios are shown in Table 4.

Table 4: Ratios between parameter estimates for separate travel time and travel cost components

	Non-commuters	Commuters
β_C vs β_T	0.94	1.20
β_{FF} vs β_{SDT}	0.90	0.80

The final part of the analysis for the base models examines the trade-offs between the various estimated parameters, giving the monetary values of changes in travel time, as well as the willingness to pay a bonus in return for avoiding congestion and road tolls. These trade-offs were calculated separately for the travel cost and road toll coefficient, where the low level of differences (cf. Table 3) needs to be recognised when comparing the results. The various trade-offs are presented in Table 5. The main differences between the two sets of trade-offs and across the two population segments arise in the greater willingness by commuters to accept increases in road tolls, and the higher

⁹ Here, it is interesting to note that a similar calculation on the cross-sectional results would lead to confidence levels of 56 percent and 92 percent for the difference between the two cost coefficients (non-commuters and commuters), and confidence levels of 92 percent and 99 percent for the two travel time coefficients. The difference between these two sets of standard errors (panel vs cross-sectional) could clearly influence a modeller's decision as to whether to use a combined coefficient. This is yet another indication of the importance of accounting for the repeated choice nature of the data.

sensitivity to slowed down time for commuters. These differences are consistent with the simple ratios (β_C/β_T , and β_{FF}/β_{SDT}) shown in Table 4.

Table 5: Willingness to pay indicators for base models

		Non-commuters	Commuters
versus β_C	β_{FF} (AUD/hour)	13.39	13.30
	β_{SDT} (AUD/hour)	14.95	16.60
	δ_{FC} (AUD)	4.89	-0.95 ⁽ⁱ⁾
	δ_T (AUD)	0.74	1.14
versus β_T	β_{FF} (AUD/hour)	12.62	15.95
	β_{SDT} (AUD/hour)	14.09	19.90
	δ_{FC} (AUD)	4.61	-1.14 ⁽ⁱ⁾
	δ_T (AUD)	0.70	1.37

⁽ⁱ⁾ Numerator of trade-off not significant beyond 25 percent level of confidence

4.2. Models using differences with respect to RP alternative

The results for the models using the specification shown in equation (5) (with additional error components) are summarised in Table 6, which, in addition to the individual parameter estimates and associated asymptotic t -ratios, also shows asymptotic t -ratios for the differences between parameter estimates associated with increases and decreases in an attribute, hence testing the validity of a symmetrical response assumption¹⁰. The validity of the assumption of an equal response to increases in the case of a zero value for the RP alternative can be evaluated on the basis of the asymptotic t -ratio (with respect to zero) associated with the additional parameter estimates $\beta_{T(inc,zero)}$, $\beta_{FF(inc,zero)}$ and $\beta_{SDT(inc,zero)}$.

It can be seen that the specification in equation (5) reduces to the specification in equation (2) in the case of a symmetrical response (i.e., $\beta_{C(dec)} = -\beta_{C(inc)}$, $\beta_{T(dec)} = -\beta_{T(inc)}$, $\beta_{FF(dec)} = -\beta_{FF(inc)}$, and $\beta_{SDT(dec)} = -\beta_{SDT(inc)}$) with no additional penalty for increases from zero (i.e., $\beta_{T(inc,zero)} = \beta_{FF(inc,zero)} = \beta_{SDT(inc,zero)} = 0$). By further noting that the models in equation (1) and (2) are formally equivalent, it can be seen that nested likelihood ratio tests can be used to compare the models in Table 2 and Table 6. The likelihood ratio test values of 88.38 and 116.66 (using the panel results) for non-commuters and commuters respectively both give p -values of 0 on the χ^2_7 distribution, suggesting a significant increase in model fit when allowing for asymmetrical response. This is also supported by the differences in the adjusted ρ^2 measures between Table 2 and Table 6, which take into account the increase in the number of parameters from 8 to 15.

¹⁰ The difference in signs between the parameters for increases and decreases was taken into account in the calculation of this t -ratio (hence working with the difference in the absolute value), which also incorporated the correlation between the two parameter estimates.

Table 6: Estimation results for model with asymmetrical response

	Non-commuters						Commuters					
	Panel		Cross-sectional			Panel		Cross-sectional				
	Coeff.	(<i>t</i> -ratio)	<i>t</i> -ratio for diff.	Coeff.	(<i>t</i> -ratio)	<i>t</i> -ratio for diff.	Coeff.	(<i>t</i> -ratio)	<i>t</i> -ratio for diff.	Coeff.		(<i>t</i> -ratio)
δ_{RP}	0.0613	(0.42)		0.1079	(1.06)	-	-0.3710	(-2.16)		-0.1993	(-1.89)	-
δ_{SPI}	0.2014	(2.87)		0.1600	(2.70)	-	0.1322	(1.86)		0.1045	(1.99)	-
$\beta_{C(dec)}$	0.5179	(6.08)	0.17	0.4497	(8.03)	0.02	0.4863	(6.39)	0.23	0.4060	(7.52)	0.25
$\beta_{C(inc)}$	-0.4930	(-4.41)		-0.4518	(-5.38)		-0.5159	(-5.63)		-0.4336	(-6.03)	
$\beta_{T(dec)}$	0.1108	(1.29)	4.99	0.1396	(2.98)	5.63	0.1858	(2.36)	2.85	0.1776	(3.86)	3.18
$\beta_{T(inc)}$	-0.7328	(-6.63)		-0.6235	(-8.93)		-0.5856	(-5.50)		-0.4439	(-7.24)	
$\beta_{T(inc,zero)}$	0.3018	(2.88)		0.2489	(3.79)	-	0.1647	(1.41)		0.0736	(1.23)	-
$\beta_{FF(dec)}$	0.0821	(8.10)	1.57	0.0723	(9.82)	1.67	0.0625	(5.06)	3.73	0.0547	(7.19)	3.56
$\beta_{FF(inc)}$	-0.1205	(-5.77)		-0.1083	(-6.64)		-0.1691	(-7.10)		-0.1335	(-8.04)	
$\beta_{FF(inc,zero)}$	0.2554	(11.77)		0.2237	(2.75)	-	0.1179	(0.89)		0.0821	(1.14)	-
$\beta_{SDT(dec)}$	0.1275	(11.10)	2.47	0.1154	(12.75)	3.35	0.1178	(13.09)	0.69	0.0988	(16.80)	0.83
$\beta_{SDT(inc)}$	-0.0504	(-1.87)		-0.0412	(-2.55)		-0.1025	(-5.41)		-0.0862	(-7.66)	
$\beta_{SDT(inc,zero)}$	0.0524	(1.01)		0.0137	(0.33)	-	-0.0811	(-2.99)		-0.1684	(-1.26)	-
δ_{FC}	0.0890	(0.45)		-0.0473	(-0.05)	-	1.0350	(1.23)		0.6770	(1.82)	-
δ_T	-0.8958	(-3.79)		-0.7196	(-5.38)	-	-0.7496	(-4.37)		-0.6177	(-5.49)	-
σ	0.6799	(12.59)					0.9117	(14.99)				
Sample	3280			3280			3792			3792		
Final LL	-2261.08			-2354.55			-2572.08			-2783.47		
Adj. ρ^2	0.3681			0.3424			0.378752			0.3283		

We now turn our attention to the actual model estimates shown in Table 6, where we again focus solely on the estimates for the panel model¹¹. Here, several differences from the base model in Table 2 can be noted straightaway. We observe a further drop in significance for δ_{RP} in the non-commuter segment, while, for commuters, the estimate is now negative, and significantly different from zero. Furthermore, we observe increases in significance for δ_{SPI} , and especially δ_T , which is now also significantly different from zero for non-commuters (which was not the case in the base model). And while there is a slight increase in significance for δ_{FC} in the commuter segment, there is a spectacular drop in the case of non-commuters. These differences are a first indication of the effects of allowing for asymmetrical response rates, leading to changes in parameters that are not in fact themselves given an asymmetrical treatment.

Consistent with intuition, the results show that increases in the various time and cost attributes are valued negatively, with the converse being the case for decreases. The very low asymptotic *t*-ratios for the difference between $\beta_{C(dec)}$ and $\beta_{C(inc)}$ show that the response to increases and decreases in travel cost is almost perfectly symmetrical. We now summarise our findings for the remaining three attributes.

¹¹ With a few exceptions, notably $\beta_{FF(inc,zero)}$ in the non-commuter segment, the use of the panel approach again leads to an upward correction of the standard errors.

- For road tolls, there is clear evidence of an asymmetrical response, with asymptotic t -ratios of 4.99 and 2.85 for non-commuters and commuters respectively. In both segments, increases in road tolls incur a bigger response than decreases, where the degree of asymmetry is more significant for non-commuters than for commuters (6.61 vs. 3.15). In both segments, increases in road toll are valued less negatively when there was no toll for the RP alternative, where $\beta_{T(\text{inc},\text{zero})}$ is however only significantly different from zero at the 84 percent level for commuters. Here, it should be noted that the RP alternative had a zero toll for 35 percent of non-commuters and for 25 percent of commuters. In these segments, the choice rate for the RP alternative is much higher (62.10 percent and 57.71 percent) than in the segment with a non-zero RP toll (31.34 percent and 24.52 percent). This would thus suggest a high reluctance for respondents to shift from a non-tolled to a tolled alternative. The apparent inconsistency of the positive estimates for $\beta_{T(\text{inc},\text{zero})}$ needs to be put in context by the negative and highly significant estimate for δ_T , which associates a further penalty with SP toll road alternatives in the case where the RP toll was zero. Finally, even after adding the positive estimate for $\beta_{T(\text{inc},\text{zero})}$ to $\beta_{T(\text{inc})}$, the response remains asymmetrical, with increases from zero carrying a more significant response than decreases from a non-zero toll.
- For free flow time, the difference between increases and decreases is only significant at the 88 percent level for non-commuters, while it is highly significant in the commuter model. In both cases, the estimate for $\beta_{\text{FF}(\text{inc},\text{zero})}$ is positive, where it is however only different from zero at the 63 percent level of confidence for commuters. In the commuter segment, the response now becomes symmetrical (increases from zero carry the same absolute response as decreases from a non-zero value). The main result in relation to $\beta_{\text{FF}(\text{inc},\text{zero})}$ however arises in the non-commuter model; here, a positive value is obtained when summing up $\beta_{\text{FF}(\text{inc})}$ and $\beta_{\text{FF}(\text{inc},\text{zero})}$, suggesting a positive effect on utility in response to increases in free flow time when this attribute was zero for the RP alternative. This however needs to be put into context by noting that increases in free flow time were (in the SP survey) generally accompanied by a decrease in slowed down time, where the positive effect of this decrease exceeds the negative effect associated with an increase in free flow time (cf., results from Table 5). In the face of a fully congested RP alternative, SP alternatives with a lower level of congestion are highly attractive, where this is captured by the positive estimate for $\beta_{\text{FF}(\text{inc},\text{zero})}$.
- For changes in slowed down time, there is evidence of an asymmetrical response for non-commuters, with the absolute response to decreases being two and a half times as large as the response to increases, showing the great appeal of reductions in congestion. The additional offset in the case of an uncongested RP alternative ($\beta_{\text{SDT}(\text{inc},\text{zero})}$) is positive for non-commuters, but not significantly different from zero at any reasonable levels of confidence. For commuters, the difference between the absolute valuation for increases and decreases is not significant beyond the 51 percent level of confidence; however, there is now a significant additional penalty in the case of an uncongested RP alternative.

As an illustration of the asymmetries observed in the two population segments, Figure 2 and Figure 3 show the impact on utility of increases and decreases in the various attributes for non-commuters and commuters respectively¹². To highlight the degree of asymmetry, the plots also show a mirror reflection of the two lines for increases and decreases through the origin.

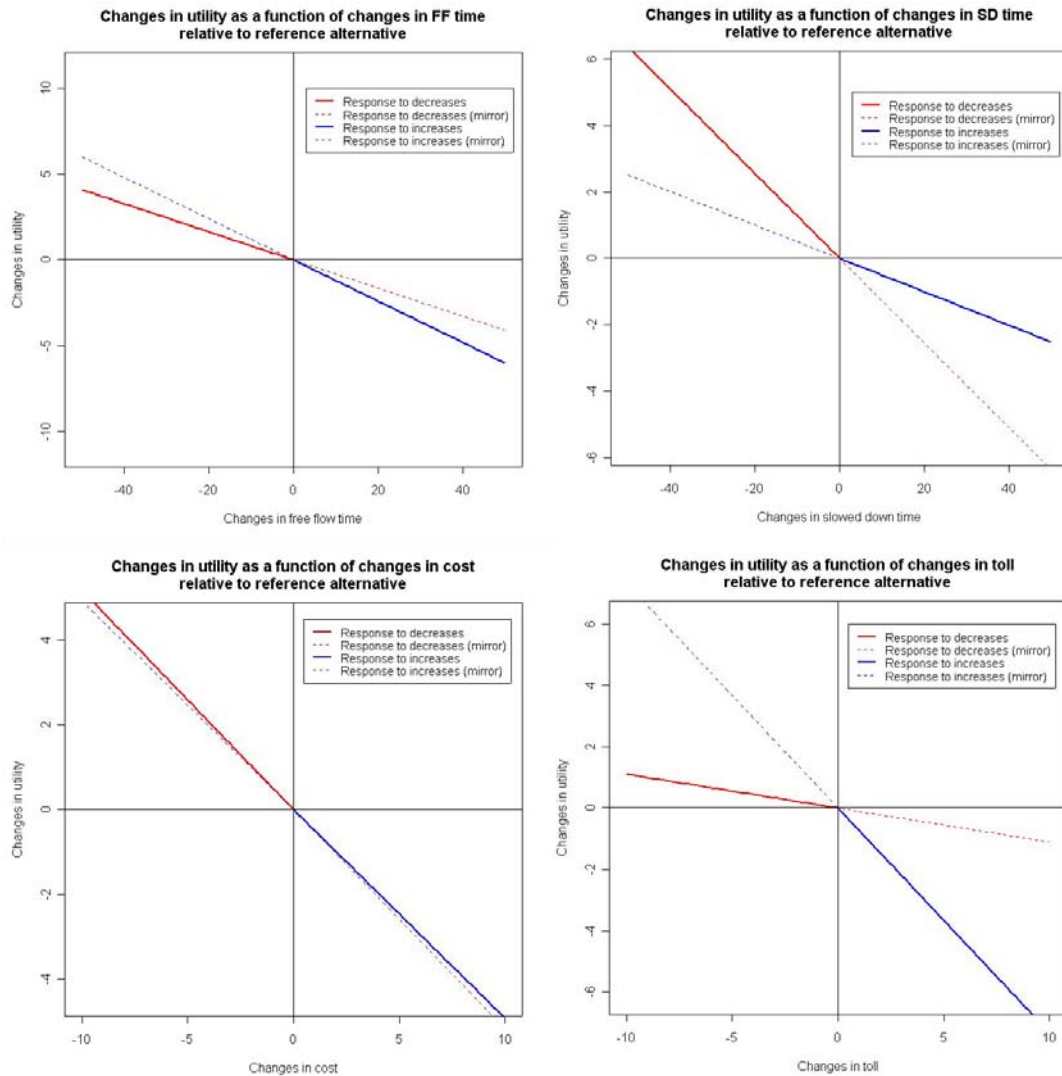


Figure 2: Evidence of asymmetrical response to changes in attributes for non-commuters

¹² The ranges used in the various plots are broadly reflective of the ranges used in the design of the SP experiments.

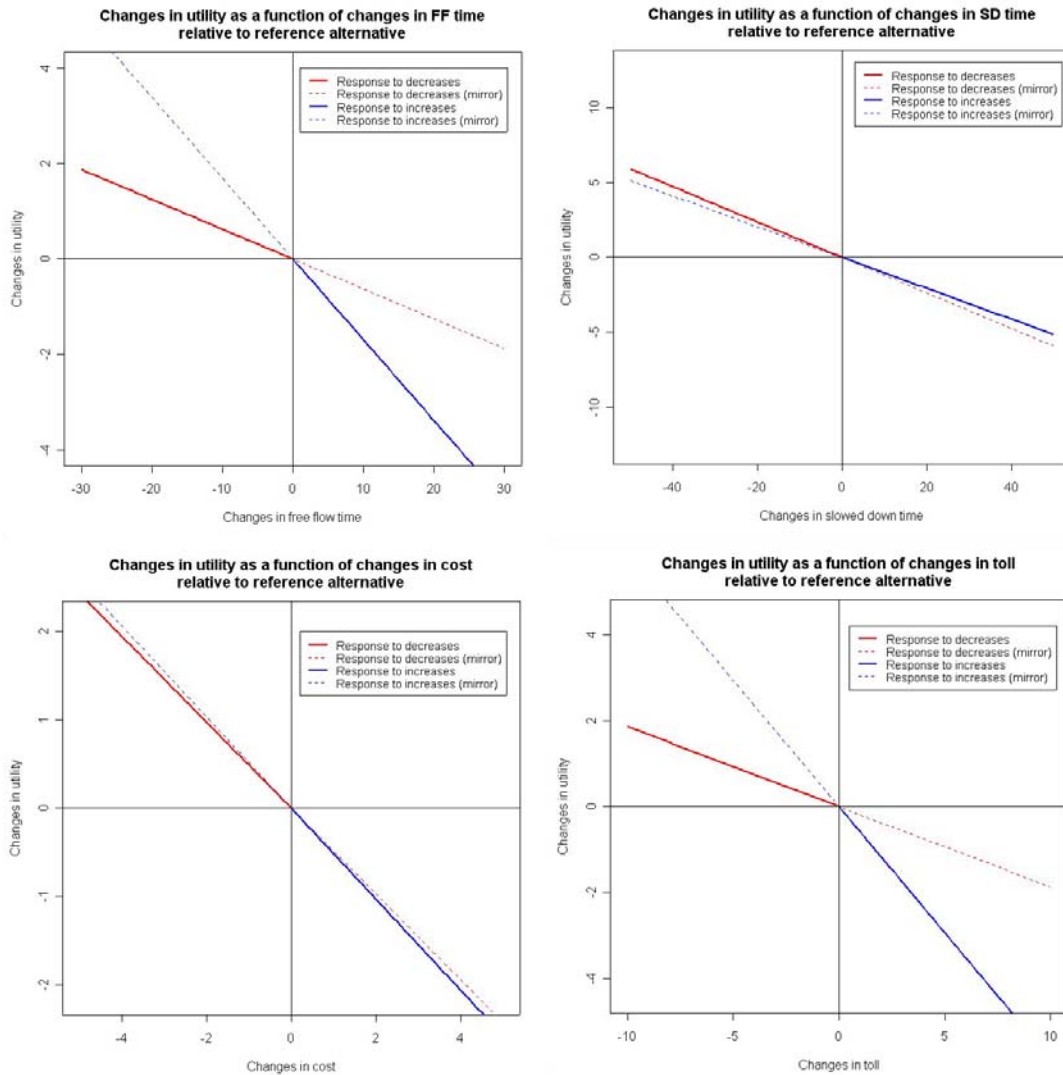


Figure 3: Evidence of asymmetrical response to changes in attributes for commuters

The next step of the analysis looks at the differences in the valuation of changes in the separate travel time and travel cost attributes, complementing the results from Table 3 for the base model. These results are summarised in Table 7, showing the asymptotic t -ratio for the differences between the coefficients for travel cost and road tolls, and free flow and slowed down time, with separate tests for increases and decreases from the RP attribute. While the results for the base model (Table 3) showed significant differences only for the two time components for commuters, a much clearer picture of differences arises when accounting for asymmetries. As seen in Table 7, there are now significant differences between the two time components for commuters as well as non-commuters, in the case of increases as well as decreases. The same is the case for decreases in the cost components (across both population groups), where only in the case of increases, there is a lack of evidence of a difference between the responses to travel cost and road tolls. These results, in comparison with those from Table 3, give an indication of the averaging error introduced by making a strict symmetry assumption in the base model, showing the benefits of the approach described in equation (5).

As a further illustration of the differences between the base model and the more advanced model, we now look at the ratios between the parameter estimates for the separate cost and time components, complementing the results from Table 4. The results, which are summarised in Table 8, are consistent with those from Table 7, and show far greater differences between the separate components than was the case in the base model (cf. Table 4). Interestingly, the results show that increases in free flow time are valued more negatively than increases in slowed down time, while decreases in slowed down time are valued more positively than decreases in free flow time. Similarly, decreases in cost are valued more positively than decreases in tolls, while increases in cost are valued less negatively than increases in tolls for non-commuters, while there is no major difference in the case of commuters.

Table 7: Asymptotic t-ratios for differences between separate travel time and travel cost coefficients

	Non-commuters	Commuters
$\beta_{C(dec)} \text{ vs } \beta_{T(dec)}$	3.38	2.75
$\beta_{C(inc)} \text{ vs } \beta_{T(inc)}$	1.70	0.51
$\beta_{FF(dec)} \text{ vs } \beta_{SDT(dec)}$	3.12	3.84
$\beta_{FF(inc)} \text{ vs } \beta_{SDT(inc)}$	2.16	2.20

Table 8: Ratios between parameter estimates for separate travel time and travel cost components

	Non-commuters	Commuters
$\beta_{C(dec)} \text{ vs } \beta_{T(dec)}$	4.67	2.62
$\beta_{C(inc)} \text{ vs } \beta_{T(inc)}$	0.67	0.88
$\beta_{FF(dec)} \text{ vs } \beta_{SDT(dec)}$	0.64	0.53
$\beta_{FF(inc)} \text{ vs } \beta_{SDT(inc)}$	2.39	1.65

The final part of the analysis looks at the trade-offs between the various parameters. The most common trade-off used in transport studies is the valuation of travel time savings (VTTS), giving the implied willingness to accept increases in travel cost in return for reductions in travel time. In a purely symmetrical model¹³, this would be given by β_{TT}/β_{TC} , where β_{TT} and β_{TC} represent the travel time and travel cost coefficients respectively. In an asymmetrical model such as those presented in this paper, the calculation is slightly different, as we now have separate coefficients for increases and decreases, suggesting different possible combinations of VTTS calculations. As an example, the willingness to accept increases in travel cost in return for reductions in free flow time would be given by $-\beta_{FF(dec)}/\beta_{C(inc)}$. This approach was used to calculate willingness to pay indicators for the two components of travel time with the two separate cost components, where trade-offs were also calculated for δ_{FC} and δ_T . The results of these calculations are summarised in Table 9, where these results are directly comparable to those presented in Table 5.

In comparison with the results for the base model, there are some significant differences. As such, the willingness to accept increases in travel cost in return for reductions in free flow time decreases by 25 percent and 45 percent for non-commuters and commuters respectively. Even more significant decreases (47 percent and 60 percent) are observed when looking at the willingness to accept increases in road tolls.

¹³ Which also uses a linear specification of utility.

While the willingness to accept increases in travel cost in return for reductions in slowed down time stays almost constant for non-commuters, it decreases by 17 percent for commuters (when compared to the base model). Finally, when using road tolls instead of travel cost, there are decreases in both population segments, by 26 percent and 39 percent respectively. These differences are yet another indication of the effects of allowing for asymmetrical response rates.

Table 9: Willingness to pay indicators for asymmetrical models

		Non-commuters	Commuters
versus β_C	β_{FF} (AUD/hour)	9.99	7.27
	β_{SDT} (AUD/hour)	15.51	13.70
	δ_{FC} (AUD)	-0.18 ⁽ⁱ⁾	-2.01 ⁽ⁱⁱ⁾
	δ_T (AUD)	1.82	1.45
versus β_T	β_{FF} (AUD/hour)	6.72	6.40
	β_{SDT} (AUD/hour)	10.44	12.07
	δ_{FC} (AUD)	-0.12 ⁽ⁱ⁾	-1.77 ⁽ⁱⁱ⁾
	δ_T (AUD)	1.22	1.28

⁽ⁱ⁾ Numerator of trade-off not significant beyond 4 percent level of confidence
⁽ⁱⁱ⁾ Numerator of trade-off not significant beyond 93 percent level of confidence

While modellers traditionally only look at trade-offs using monetary coefficients in the denominator, it is similarly interesting to use them in the numerator, giving the willingness to accept increases in some other attribute, such as travel time, in return for decreases in monetary attributes, such as travel cost or road tolls. In the case of a purely symmetrical model, these trade-offs are simply the inverse of the standard indicators such as VTTS. As such, the results from Table 5 can be used to obtain the implied willingness to accept increases in free flow time in return for decreases in travel cost by taking the simple inverse. A multiplication by 60 transforms the results to minutes per dollar as opposed to hours per dollar. The results of this calculation are shown in Table 10, where the additional constants δ_{FC} and δ_T are not used.

Table 10: Willingness to accept increases in travel time in return for decreases in travel cost or road tolls for base model (min/AUD)

		Non-commuters	Commuters
versus β_C	β_{FF}	4.48	4.51
	β_{SDT}	4.01	3.62
versus β_T	β_{FF}	4.75	3.76
	β_{SDT}	4.26	3.02

In the case of an asymmetrical model, the calculation is different, as we now have separate coefficients for decreases in the two cost attributes as well as for increases in the two travel time attributes. As such, the willingness to accept increases in free flow time in return for reductions in travel cost is now given by $-\beta_{C(dec)}/\beta_{FF(inc)}$. The results of this calculation are shown in Table 11, where the additional constants δ_{FC} and δ_T are again not used, and where no additional trade-offs are calculated for increases in free flow and slowed time from zero.

In comparison with the results from Table 10, the first observation relates to a drop in the willingness of commuters to accept increases in free flow time in return for decreases in travel cost, where this is now lower than the corresponding trade-off for non-commuters. The differences to the base model are even more significant when looking at the willingness to accept increases in slowed down time in return for reductions in travel cost, especially for non-commuters, where there is a more than 250 percent increase. On the other hand, for the willingness to accept increases in free flow time or slowed down time in return for reductions in road tolls, there is now a major decrease in both population segments.

Table 11: Willingness to accept increases in travel time in return for decreases in travel cost or road tolls for asymmetrical models (min/AUD)

		Non-commuters	Commuters
versus β_C	β_{FF}	4.30	2.88
	β_{SDT}	10.29	4.74
versus β_T	β_{FF}	0.92	1.10
	β_{SDT}	2.20	1.81

5. Conclusions

This paper has summarised an analysis allowing for asymmetrical response to increases and decreases in attributes describing alternatives in a discrete choice context. Our analysis supports the existence of framing effects in SP data and suggests that preference formation may not relate to the absolute values of the attributes shown in SP experiments, but rather to differences from respondent specific reference points. In the two SP studies reported here (one commuter, the other non-commuter), the results suggest that respondents' preferences are asymmetrical for a number of attributes in terms of whether an attribute was framed positively or negatively relative to each respondent's point of reference. This strongly supports the prospect theory view of how decisions are made, namely that utility functions depend on *changes* in the values of alternatives (attributes) rather than the actual values of the alternatives (attributes) themselves. Put another way, our findings suggest that utility is derived from the mental returns (not necessarily monetary) associated with alternatives and not the net mental worth of the alternative to decision makers. The findings, however, do not support the exact supposition put forward by prospect theory that the value function for losses should be convex and relatively steep whilst the value function for gains losses would

be expected to be concave and not quite so steep. We found different relationships between gains and losses for different attributes. This can potentially be explained by the nature of the survey data, in which individual attributes are not assessed independently by respondents, but are traded off against each other. The interaction between free flow time and slowed down time potentially also plays a role in this.

Although we have used a specific type of SP experiment relating the SP alternatives of the experiment to respondent specific RP alternatives via pivoted designs, our findings are in line with those of other researchers using more conventional experiments, who found that differences in preference space between alternatives impact upon the results found in SP studies (e.g., Mazzota and Opaluch 1995; Swait and Adamowicz 1996; DeShazio and Fermo 2002). We are therefore confident that our findings may be extended beyond pivot type designs; although we caution that more research to confirm this is required.

However, caution is required in the interpretation of the results. Indeed, whilst the results of our modelling support the existence of asymmetrical marginal utilities when allowing for relative change of direction in the attributes, before we can confirm this, it is necessary to rule out the possibility that the results obtained are not due to non-linearity in the marginal utility rather than in the relative direction of the attribute relative to the base. To test this possibility, a number of models were estimated that made use of various non-linear transforms of the base attributes, such as for example with the help of a power function. The results obtained from these models suggested that transformations of the attributes were not warranted, that is, there was no evidence of significant and consistent non-linearities, reflected also in low improvements in model fit when using these approaches (when compared to the asymmetrical formulation)¹⁴.

While, as mentioned in the introduction, a number of existing VTTS studies have allowed for asymmetrical response to gains and losses, the lack of dissemination of such material means that the use of a purely symmetrical approach is still commonplace. This alone is sufficient motivation for our attempts at reanalysing the benefits of an asymmetrical approach. Additionally however, our analysis differs from previous studies both from a data perspective as well as from a methodological one. Firstly, the dataset used here includes the actual reference alternative in each single choice set, meaning that the reference values used in the analysis were actually presented to respondents during the survey. Secondly, the dataset makes use of two separate travel time and two separate travel cost components, while previous research has generally relied on a single component along each dimension. Thirdly, unlike previous studies, we not only allow for an asymmetrical response to increases and decreases, but also allow for a difference in the response when a given variable has a zero value for the reference alternative.

At this point, it is also of interest to briefly look back at the issue of the *inertia* term discussed by Bates and Whelan (2001). As mentioned in the introduction, it had been observed that the inclusion of a constant associated with the reference alternative significantly decreased the degree of asymmetry in the results. In our study, no such effect was observed. In fact, the inclusion or otherwise of the RP constant had little or no effect on the degree of asymmetries, and the actual estimate of the constant was not

¹⁴ We thank Kenneth Train for alerting us to this possibility, and suggesting this test. The model results are available upon request.

significantly different from zero in one of the two population segments. This suggests that the relationship between this constant and the asymmetries is dataset-dependent.

This paper offers new evidence to reinforce the case for examining asymmetrical preferences, within a discrete choice framework. Future research is required to test whether the model results hold for more advanced discrete choice models, such as mixed logit. Indeed, it may be true that the results observed here may be partly due to the presence of unexplained taste heterogeneity. However, it may be equally true that asymmetry in the preference for an attribute may be exacerbated further, with different respondents placing different psychological weights on gains and losses. An another avenue for future research is the exploration of non-linearities in response in conjunction with an asymmetrical treatment; initial results show the presence of non-linearities to either side of the origin, where the degree and shape of non-linearities vary across directions as well as attributes.

In closing, the empirical evidence presented in this paper supports a case for estimating separate willingness to pay measures (e.g., VTTS) for relative gains or losses associated with either new levels of service offerings or completely new alternatives. Such a move has wider implications for how such willingness to pay measures are used beyond SP contexts. For example, SP derived VTTSs are commonly used in network models to evaluate the economic viability of proposed infrastructure development such as the building of new toll roads. These network models typically can only handle a single (or at most a few) VTTS values (and typically cannot handle the full VTTS distributions). Using the methodology explained here would require that transport network models be able to handle multiple VTTS values, and do so in such a way that modelled trips could be assigned VTTS values corresponding to whether the trip would be expected to represent a gain or a loss in terms of the travel time and cost component of the trip relative to the simulated trip maker's previous experiences. This is a non-trivial task, but the benefits of such an approach in terms of forecasting accuracy are potentially very significant.

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