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

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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 this paper we investigate the presence of asymmetry in preferences to test for reference 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, where the degree of asymmetry varies across attributes and population segments.

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Keywords: willingness to pay, asymmetric preferences, referencing, stated choice, discrete choice, value of travel time savings

1. Introduction

The calculation 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. The case of travel time savings is of particular interest. Given the importance of valuation of travel time savings (VTTS) measures in transport planning, it should come as no surprise that there is an ever increasing body of research looking at ways of representing the behavioural plausibility of VTTS estimates.

While the representation of inter-agent taste heterogeneity and the relationship between respondents' socio-demographic attributes and their WTP measures has been the topic of an ever increasing number of studies (see for example, Algers *et al.*, 1998, Hensher and Greene, 2003, Fosgerau, 2005 and Hess *et al.*, 2005), comparatively little effort has gone into analysing how respondents process the attributes describing the alternatives in Stated Preference (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 Hensher (2006a, 2006b).

This paper looks at one specific 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 alternative[1]. We estimate models that incorporate different parameters associated with

[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.

attribute levels that are either higher or lower than the base reference alternative level. This allows us to test whether respondents' preferences for an attribute are different depending on whether an attribute is either specified negatively or positively around the reference or neutral point. The use of the referencing 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, Hensher *et al.* 2005; Train and Wilson 2006).

The use of a referencing approach relates the work described in this paper to prospect theory (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. 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 referencing 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 differences 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 modelling approach used in this paper contrasts with that used typically in discrete choice analyses in which the utility of an alternative is a function of the tastes of the respondents and the absolute attributes of the alternative. While the research described in this paper presents a departure from the status quo in VTTS analyses, it should be noted that this applies primarily to the *published* state of practice. Several existing VTTS studies have allowed for an asymmetrical response to gains and losses in travel time and travel cost (HCG 1990, 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]. Other examples of an application allowing for asymmetrical preference formation are Suzuki et al. (2001) in an air travel context and van Ryzin (2005), who briefly touches on differences in response to losses and gains in a revenue management context 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.

This paper 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. The research, however, does also differ somewhat from previous efforts accounting for differences in the response to gains and losses. Indeed, existing work has seemingly always been based on a simplistic survey design making use of two variables only, travel time and travel cost, with one alternative being less expensive while the other is faster. The data in this paper uses two separate travel time components (free flow and slowed down) as well as two separate travel cost

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

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 situation[3]. 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.

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. 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)[4].

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

[4] 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).

The SP questionnaire presented respondents with sixteen choice situations, each giving a choice between their current (reference) route and two alternative routes with varying trip attributes. A statistically efficient design was used in the generation of the SP questionnaires (see for example, Bliemer *et al.*, 2006). 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 VTTS studies undertaken by Hensher (2001). All attributes of the two unlabelled SP alternatives are based on the values of the current trip. An example of a stated choice screen, for the current trip (or reference) alternative and two design–generated combinations of actual attribute levels is shown in Figure 1.

Insert Figure 1

Unlike most SP experiments where the attributes are fixed for the sampled population, the linking of the attribute levels to a recently experienced trip for each respondent meant that the attribute levels for the experiment were not known in advance of the survey. For this reason, prior to data collection, it became necessary to assume attribute levels as well as prior parameter values when constructing the design. Table 1 shows the attribute levels and percentages used to construct each of the experimental designs (see Bliemer *et al.* 2006 for details). The survey designs are available from http://www.itls.usyd.edu.au/about_itls/staff/johnr.asp. A final sample of 442 effective interviews was obtained (237 commuters and 205 non-commuters), which, with each person responding to 16 choice sets, resulted in 3,792 commuter and 3,280 non-commuter observations for model estimation.

Insert Table 1

A possible criticism that could be levelled at our study is that the data used was not collected with the specific aim of testing for the effects of asymmetrical preference formation. The aim of this paper is however not simply to introduce a certain modelling approach and to then test it on the first available dataset. Rather, we discuss a phenomenon that potentially plays a role in many existing datasets (given the reliance on pivot designs), and illustrate the effects of this phenomenon on a standard dataset that is representative of the type of survey data used in so many existing studies.

3. Description of approach

In the analysis, only four of the five attributes used in the SP design were used, where trip time variability over repeated trips was excluded[5]. While the use of an asymmetrical modelling approach does constitute a non-linear specification of the utility function, the actual marginal utility coefficients all interact linearly with the associated attributes (i.e., the increases or decreases in an attribute in the case of an asymmetrical approach). The findings in terms of the degree of asymmetry could potentially be masked by the presence of non-linearities in the interaction between say the travel time coefficient and the travel time attribute. Indeed, it is conceivable that any indication of asymmetrical preference formation is due to non-linearity in the

[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.

marginal utility rather than in the relative direction of the attribute relative to the base[6]. 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, increasing the reliability of our findings in relation to asymmetrical preference formation[7].

3.1. Symmetrical modelling approach

In a linear model, the observed utility of alternative *i* is given by:

$$V_i = \delta_i + \delta_{T(i)} + \delta_{FC(i)} + \beta_{FF} FF_i + \beta_{SDT} SDT_i + \beta_C C_i + \beta_T T_i \qquad [1]$$

where δ_i is a constant associated with alternative *i* (normalised to zero for the third alternative[8]), and β_{FF}, β_{SDT}, β_C and β_T are the coefficients associated with free flow travel time (FF), slowed-down travel time (SDT), running cost (C), and road tolls (T) respectively. Travel time attributes are expressed in minutes, while travel cost attributes are expressed in Australian dollars ($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).

[6] We thank Kenneth Train for alerting us to this possibility, and suggesting this test. The model results are available upon request.
[7] Detailed results are available from the first author on request.
[8] 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. Asymmetrical approach

The above specification can be easily adapted to work with differences in relation to a reference or RP (revealed preference) alternative, as opposed to using the absolute values presented to respondents in the SP experiments. For the reference alternative *r*, the utility function is rewritten to include only the three dummy variables δr (ASC), $\delta_{T(r)}$ (toll road dummy) and $\delta_{FC(r)}$ (fully congested dummy). For SP alternative *j* (where $j \neq r$), the observed utility function is given by:

$$V_{j,new} = \delta_j + \delta_{T(j)} + \delta_{FC(j)}$$
$$+ \beta_{FF(inc)}\max(FF_j\text{-}FF_r,0) + \beta_{FF(dec)}\max(FF_r\text{-}FF_j,0)$$
$$+ \beta_{SDT(inc)}\max(SDT_j\text{-}SDT_r,0) + \beta_{SDT(dec)}\max(SDT_r\text{-}SDT_j,0)$$
$$+ \beta_{C(inc)}\max(C_j\text{-}C_r,0) + \beta_{C(dec)}\max(C_r\text{-}C_j,0)$$
$$+ \beta_{T(inc)}\max(T_j\text{-}T_r,0) + \beta_{T(dec)}\max(T_r\text{-}T_j,0) \qquad [2]$$

This specification is obtained through taking differences for the four attributes relative to the reference alternative, where separate coefficients are estimated for increases (inc) and decreases (dec), hence allowing for asymmetrical responses.

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. We now have:

$$V_{j,new} = \delta_j + \delta_{T(j)} + \delta_{FC(j)}$$
$$+ \beta_{FF(inc)}\max(FF_j\text{-}FF_r,0) + \beta_{FF(inc,zero)}FF_j \cdot I_0(FF_r) + \beta_{FF(dec)}\max(FF_r\text{-}FF_j,0)$$
$$+\beta_{SDT(inc)}\max(SDT_j\text{-}SDT_r,0) + \beta_{SDT(inc,zero)}SDT_j \cdot I_0(SDT_r) + \beta_{SDT(dec)}\max(SDT_r\text{-}SDT_j,0)$$
$$+ \beta_{C(inc)}\max(C_j\text{-}C_r,0) + \beta_{C(dec)}\max(C_r\text{-}C_j,0)$$
$$+ \beta_{T(inc)}\max(T_j\text{-}T_r,0) + \beta_{T(inc,zero)}T_j \cdot I_0(T_r) + \beta_{T(dec)}\max(T_r\text{-}T_j,0) \quad [3]$$

where, as an example, I_0(Tr) is equal to one only if the reference alternative is a toll-free alternative. From the above, it can be seen that $\beta_{T(inc)}$ will be estimated for all increases, including those from zero, while the additional coefficient $\beta_{T(inc,zero)}$ is only estimated for increases from zero. As such, $\beta_{T(inc,zero)}$ represents a bonus that needs to be added to $\beta_{T(inc})$ when Tr is zero. Here, it should be said that a zero value for the free flow attribute (i.e. fully congested RP journey) is very rare in this dataset; in fact, it only occurs for 1.9% of respondents. On the other hand, for 3.6% of respondents, we have a zero value for SDT in the reference alternative, such that $\beta_{SDT(inc,zero)}$ is estimated. Finally, 29.8% of respondents used a toll-free alternative for the observed trip, such that $\beta_{T(inc,zero)}$ was estimated for just over a third of respondents.

Here, it should be noted that while equation [3] has 7 additional parameters when compared to equation [1], the resulting increase in model complexity is very small. Indeed, the model is still purely linear, and the a priori data transformations required are minimal. The resulting model structure is still very easy to estimate and also apply, which is crucial for practical large-scale modelling analyses.

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. Not accounting for the possible correlation between the behaviour of a given respondent across the individual choice situations can potentially have a significant effect 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[9] to account for individual specific correlation[10].

With $V_{n,t,RP,base}$, $V_{n,t,SP1,base}$, and $V_{n,t,SP2,base}$ giving the base utilities for the three alternatives[11] for respondent n and choice situation t, the final utility function (for respondent n and choice situation t) is given by:

$$U_{n,t,RP} = V_{n,t,RP,base} + \theta\, \xi_{n,RP} + \varepsilon_{n,k,RP}$$

$$U_{n,t,SP,1} = V_{n,t,SP1,base} + \theta\, \xi_{n,SP1} + \varepsilon_{n,k,SP1}$$

$$U_{n,t,SP,2} = V_{n,t,SP2,base} + \theta\, \xi_{n,SP2} + \varepsilon_{n,k,SP2} \qquad [4]$$

[9] Our method differs from the commonly used approach of capturing serial correlation with a random coefficients formulation where tastes are assumed to vary across respondents but remain constant across observations for the same respondent. This approach not only makes the considerable assumption of an absence of inter-observational variation (cf. Hess & Rose, 2006), but the results are potentially also affected by confounding between serial correlation and random taste heterogeneity.

[10] We thank Andrew Daly for this suggestion.

[11] Independently of which specification is used, i.e. models based on equation [1] or equation [3].

where $\varepsilon_{n,k,RP}$, $\varepsilon_{n,k,SP1}$, and $\varepsilon_{n,k,SP2}$ are the usual IID draws from a type I extreme value distribution, and $\xi_{n,RP}$, $\xi_{n,SP1}$ and $\xi_{n,SP2}$ are draws from three independent Normal variates with a zero mean and a standard deviation of 1. To allow for correlation across replications for the same individual, *the integration over these latter three variates 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 (i.e., $\xi_{n,RP}$, $\xi_{n,SP1}$ and $\xi_{n,SP2}$) 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.

Letting $j_{n,t}$ refer to the alternative chosen by respondent n in choice situation t (with t=1,…,T), the contribution of respondent n to the log-likelihood function is then given by:

$$LL_n = \ln\left(\int_{\xi_n}\left(\prod_{t=1}^{T} P\left(j_{n,t} \middle| V_{n,t,RP,base}, V_{n,t,SP1,base}, V_{n,t,SP2,base}, \xi_{n,RP}, \xi_{n,SP1}, \xi_{n,SP2}, \theta\right)\right) f\left(\xi_n\right) d\xi_n\right) \quad [5]$$

where ξ_n groups together $\xi_{n,RP}$, $\xi_{n,SP1}$ and $\xi_{n,SP2}$ and where $f\left(\xi_n\right)$ refers to the joint distribution of the elements in ξ_n, with a diagonal covariance matrix.

This model with error components for each alternative is identified. Unlike other specifications (e.g., Ben-Akiva *et al.* 2001) that apply the results to identifying the scale factors in the disturbances in the marginal distributions of the utility functions, the logic does not apply to identifying the parameters on the attributes; and in the conditional distribution we are looking at here, the error components are acting like attributes, not disturbances. We are estimating the θ parameters as if they were weights on attributes, not scales on disturbances, and hence the way that the conditional distribution is presented. The parameters are identified in the same way that the βs on the attributes are identified. Since the error components are not observed, their scale is not identified. Hence, the parameter on the error component is ($\delta_m\sigma_m$), where σ_m is the standard deviation. Since the scale is unidentified, we would normalize it to one for estimation purposes, with the understanding that the sign and magnitude of the weight on the component are carried by θ. But, neither is the sign of δ_m identified, since the same set of model results will emerge if the sign of every draw on the component were reversed – the estimator of δ would simply change sign with them. As such, we normalize the sign to plus. In sum, then, we estimate $|\delta_m|$, with the sign and the value of σ_m normalized for identification purposes.

All models were coded and estimated in Ox 4.2 (Doornik, 2001), and the error-components models were estimated using 2,000 modified latin hypercube sampling (MLHS) draws (Hess et al., 2006)[12]. 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 [4].

The inclusion of the error components for panel effects is independent of the treatment of asymmetries in response. As such, analysts will still be able to estimate

[12] The asymmetric model specification accounting for the panel nature of the data can also be estimated using popular software packages such as nlogit 4.

models offering an asymmetrical treatment of preference formation without having to adapt their estimation code to deal with the repeated choice nature of the data.

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 [3], with the additional panel error components, as set out in equation [4].

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. In each case, the results for a cross-sectional model are presented alongside those for the *panel* model, with the difference being the inclusion of the θ term (as set out in Section 3.4.). Finally, for all models, two measures of model fit are shown in addition to the log-likelihood, namely the adjusted ρ^2 measure[13] and the corrected Akaike Information Criterion (AICc[14])

Insert Table 2

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[13] Calculated as $1-\frac{LL(\hat{\beta})-p}{LL(0)}$, where $LL(\hat{\beta})$ gives the log-likelihood at convergence, $LL(0)$ gives the log-likelihood at zero, and *p* gives the number of estimated parameters.

[14] The AICc is given by $-2LL(\hat{\beta})+2\frac{Np}{N-p-1}$ where *N* gives the number of observations.

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 statistically 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 [4]. 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 (θ). 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 (see for example Cirillo et al., 2000) 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 is consistent with 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 [4].

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.

Insert Table 3

The results show that the difference between the two cost coefficients (travel cost and road toll) is not significant at the 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 commuters.

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.

It is also informative to look at the difference in sensitivity to the two travel time and travel cost coefficients (**Error! Reference source not found.**). A simple calculation using 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. With these ratios, it is important to keep the high standard errors for differences in mind (Table 3).

Insert Table 4

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 (i.e., δ_{FF}/β_C, δ_{SDT}/β_C, δ_{Ff}/β_T and δ_{SDT}/β_T), as well as the willingness to pay a bonus in return for avoiding congestion and road tolls (i.e., δ_{FC}/β_C and δ_{FC}/β_T). These trade-offs were calculated separately for the travel cost (β_C) and road toll (β_T) coefficient, where the low level of differences (cf. Table 3 and **Error! Reference source not found.**) 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 road tolls (i.e., $1.14 vs $0.74 and $1.37 vs $0.70), and the higher sensitivity to slowed down time for commuters (i.e., $16.60 vd $14.95 and $19.9 vs $14.09). These differences are consistent with the simple ratios (β_C/β_T, and β_{FF}/β_{SDT}) shown in **Error! Reference source not found.**.

Insert Table 5

4.2. Models using differences with respect to RP alternative

The results for the models using the specification shown in equation [3] (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 assumption[15]. 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 [3] reduces to the specification in equation [1] in the case of a symmetrical response. As such, 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

[15] 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.

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.

We now turn our attention to the model estimates shown in Table 6, where we again focus on the estimates for the panel model[16]. Here, several differences from the base model in Table 2 can be noted. 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_{SP1}, and especially δ_{T}, which is now also significantly different from zero for non-commuters (which was not the case in the base model). Although there is a slight increase in significance for δ_{FC} in the commuter segment, there is a drop in the case of non-commuters. These differences indicate the value of allowing for asymmetrical response rates.

Insert Table 6

Consistent with intuition, the results show that increases in the 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 the findings for the remaining three attributes.

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 greater response than decreases, where the

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

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 $\beta_{\text{T(inc,zero)}}$ 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 positive estimates for $\beta_{\text{T(inc,zero)}}$ 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, after adding the positive estimate for $\beta_{\text{T(inc,zero)}}$ to $\beta_{\text{T(inc)}}$, 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 $\beta_{\text{FF(inc,zero)}}$ is positive; however it is 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 statistically significant result in relation to $\beta_{\text{FF(inc,zero)}}$ arises in the non-commuter model; here, a positive value is obtained when summing up $\beta_{\text{FF(inc)}}$ and $\beta_{\text{FF(inc,zero)}}$, 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. 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 $\beta_{FF(inc,zero)}$.

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 ($\beta_{SDT(inc,zero)}$) 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 additionally 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 respectively[17]. To highlight the degree of asymmetry, the plots also show a mirror reflection of the two lines for increases and decreases through the origin.

Insert Figure 2

[17] The ranges used in the various plots are broadly reflective of the ranges used in the design of the SP experiments.

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 [3].

Insert Figure 3

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. 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.

Insert Tables 7 and 8

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 model[18], 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-

[18] Which also uses a linear specification of utility.

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. 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.

Insert Table 9

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. Appropriate values for the symmetrical model, obtained on the basis of the results from Table 5 are shown in Table 10.

Insert Table 10

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 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.

Insert Table 11

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 referencing around an experienced alternative 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.

The approach discussed herein presents a relatively straightforward extension of typical modelling practice, with potentially significant improvements in model accuracy. Indeed, the asymmetries in response can be accounted for through the inclusion of a few additional parameters, without requirements for a mathematically difficult formulation or computer-intensive estimation process. This is not the case for other improvements, such as for example the use of random coefficients models. These approaches, while popular in academic research, have found little application in actual *real-world*, studies, due to the high cost of estimation and application. Finally, it can be expected that accounting for asymmetries in response potentially reduces the scope for retrieving random taste heterogeneity, by explaining a bigger part of the unobserved part of utility. This thus not only lowers the requirements for random coefficients approaches, but also explains a bigger share of the behavioural patterns in a deterministic fashion, which is clearly preferable.

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 referenced positively or negatively relative to each respondent's point of reference. This strongly supports the position that utility functions depend on *changes* in the values of alternatives (attributes) rather than the actual values of the alternatives (attributes) themselves.

The findings, however, do not support the supposition from prospect theory that the value function for losses should be convex and relatively steep whilst the value function for gains 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. This is an important finding, suggesting that when attribute packages are being evaluated, the role of a specific attribute is assessed relative to its positioning in a package, and between the package and the reference package. We believe that we are seeing the role of bounded rationality and the risk that SP experiments offer attribute level *mixes* that are outside of the acceptable bounds on one or more attributes. There is a need for further research on the role that attribute mixes have on the way that specific attributes are processed.

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; DeShazo 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.

Finally, it is also of interest to briefly look at the issue of the *inertia* term discussed by Bates and Whelan (2001). It has 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 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.

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.

Several avenues for further research can be identified. These include the testing for asymmetrical preference formation in more advanced model structures, such as GEV nesting structures, or GEV mixture models. Finally, it is of interest to test for non-linearities in asymmetrical response rates, allowing for differences in the degree and shape of non-linearities to either side of the origin.

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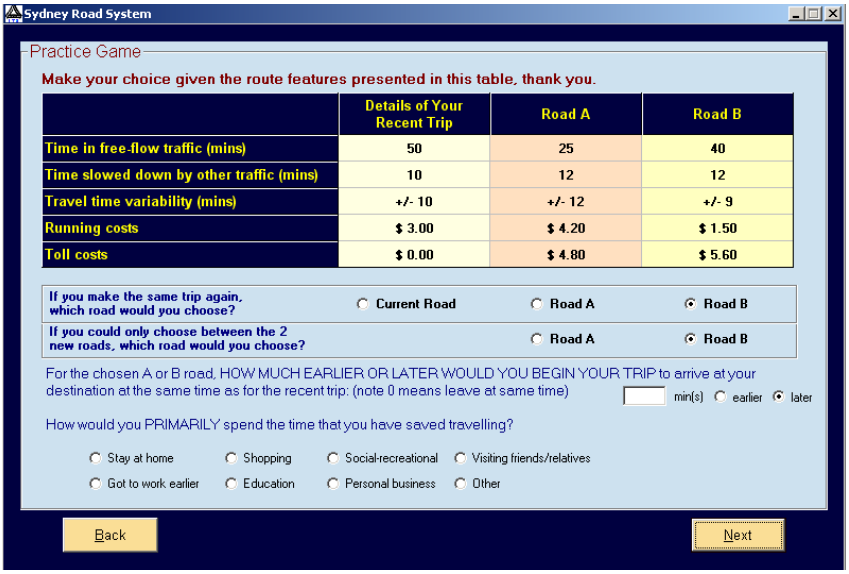

Figure 1: An example of a stated choice screen

Table 1: Experimental Design Attribute levels and Pivot Percentages

(a) Attribute levels Assumed					
Trip segment	**Free flow time**	**Slowed down time**	**Variability**	**Running costs**	**Toll costs**
< 30 mins	10	5	5	$2.00	$2.00
31-60 mins	30	15	8	$3.50	$2.00
61+ mins	40	20	10	$5.00	$2.00
(b) Pivot Percentages					
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%

Table 2: Estimation results for base models

	Non-commuters				Commuters			
	Panel		Cross-sectional		Panel		Cross-sectional	
	Coeff.	(*t*-ratio)	Coeff.	(*t*-ratio)	Coeff.	(*t*-ratio)	Coeff.	(*t*-ratio)
RP specific constant (δ_{RP})	0.1957	(1.44)	0.1779	(2.38)	0.0692	(0.54)	0.1480	(2.28)
SP alternative 1 constant (δ_{SP1})	0.1896	(2.74)	0.1527	(2.58)	0.1107	(1.62)	0.0843	(1.62)
Running cost (β_C)	-0.4129	(-9.21)	-0.3673	(-12.81)	-0.4119	(-11.60)	-0.3430	(-13.92)
Toll cost (β_T)	-0.4381	(-4.18)	-0.4099	(-8.14)	-0.3435	(-5.30)	-0.2686	(-6.98)
Free flow time (β_{FF})	-0.0921	(-11.22)	-0.0815	(-17.76)	-0.0913	(-10.06)	-0.0749	(-16.65)
Slowed down time (β_{SDT})	-0.1029	(-12.25)	-0.0928	(-17.16)	-0.1139	(-16.01)	-0.0954	(-26.07)
Congested time only dummy (δ_{FC})	-2.0184	(-14.93)	-1.9460	(-2.07)	0.3916	(0.63)	0.0720	(0.31)
A toll is charged dummy (δ_T)	-0.3068	(-0.77)	-0.1544	(-0.76)	-0.4712	(-1.92)	-0.5060	(-3.24)
θ	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	
AICc	4628.59		4809.46		5278.87		5726.49	

Table 3: Asymptotic *t*-ratios for differences between separate travel time and travel cost coefficients (panel specification for symmetrical model)

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

Table 4: Ratios between parameter estimates for separate travel time and travel cost components (panel specification for symmetrical model)

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

Table 5: Willingness to pay indicators for base models using panel specification

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

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

Table 6: Estimation results for model with asymmetrical response

	Non-commuters						Commuters					
	Panel			Cross-sectional			Panel			Cross-sectional		
	Coeff.	(*t*-ratio)	*t*-ratio for diff.	Coeff.	(*t*-ratio)	*t*-ratio for diff.	Coeff.	(*t*-ratio)	*t*-ratio for diff.	Coeff.	(*t*-ratio)	*t*-ratio for diff.
RP specific constant (δ_{RP})	0.0613	(0.42)	-	0.1079	(1.06)	-	-0.3710	(-2.16)	-	-0.1993	(-1.89)	-
SP alternative 1 constant (δ_{SP1})	0.2014	(2.87)	-	0.1600	(2.70)	-	0.1322	(1.86)	-	0.1045	(1.99)	-
Running cost decrease ($\beta_{C(dec)}$)	0.5179	(6.08)	0.17	0.4497	(8.03)	0.02	0.4863	(6.39)	0.23	0.4060	(7.52)	0.25
Running cost increase ($\beta_{C(inc)}$)	-0.4930	(-4.41)		-0.4518	(-5.38)		-0.5159	(-5.63)		-0.4336	(-6.03)	
Toll cost decrease ($\beta_{T(dec)}$)	0.1108	(1.29)	4.99	0.1396	(2.98)	5.63	0.1858	(2.36)	2.85	0.1776	(3.86)	3.18
Toll cost increase ($\beta_{T(inc)}$)	-0.7328	(-6.63)		-0.6235	(-8.93)		-0.5856	(-5.50)		-0.4439	(-7.24)	
Toll cost diff is zero ($\beta_{T(inc,zero)}$)	0.3018	(2.88)	-	0.2489	(3.79)	-	0.1647	(1.41)	-	0.0736	(1.23)	-
Free flow time decrease ($\beta_{FF(dec)}$)	0.0821	(8.10)	1.57	0.0723	(9.82)	1.67	0.0625	(5.06)	3.73	0.0547	(7.19)	3.56
Free flow time increase ($\beta_{FF(inc)}$)	-0.1205	(-5.77)		-0.1083	(-6.64)		-0.1691	(-7.10)		-0.1335	(-8.04)	
Free flow diff is zero ($\beta_{FF(inc,zero)}$)	0.2554	(11.77)	-	0.2237	(2.75)	-	0.1179	(0.89)	-	0.0821	(1.14)	-
Slowed down time decrease ($\beta_{SDT(dec)}$)	0.1275	(11.10)	2.47	0.1154	(12.75)	3.35	0.1178	(13.09)	0.69	0.0988	(16.80)	0.83
Slowed down	-0.0504	(-1.87)		-0.0412	(-2.55)		-0.1025	(-5.41)		-0.0862	(-7.66)	

time increase ($\beta_{SDT(inc)}$)												
$\beta_{SDT(inc,zero)}$	0.0524	(1.01)	-	0.0137	(0.33)	-	-0.0811	(-2.99)	-	-0.1684	(-1.26)	-
Congested time only dummy (δ_{FC})	0.0890	(0.45)	-	-0.0473	(-0.05)	-	1.0350	(1.23)	-	0.6770	(1.82)	-
A toll is charged dummy (δ_T)	-0.8958	(-3.79)	-	-0.7196	(-5.38)	-	-0.7496	(-4.37)	-	-0.6177	(-5.49)	-
θ	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		
AICc	4554.33			4739.25			5176.30			5597.07		

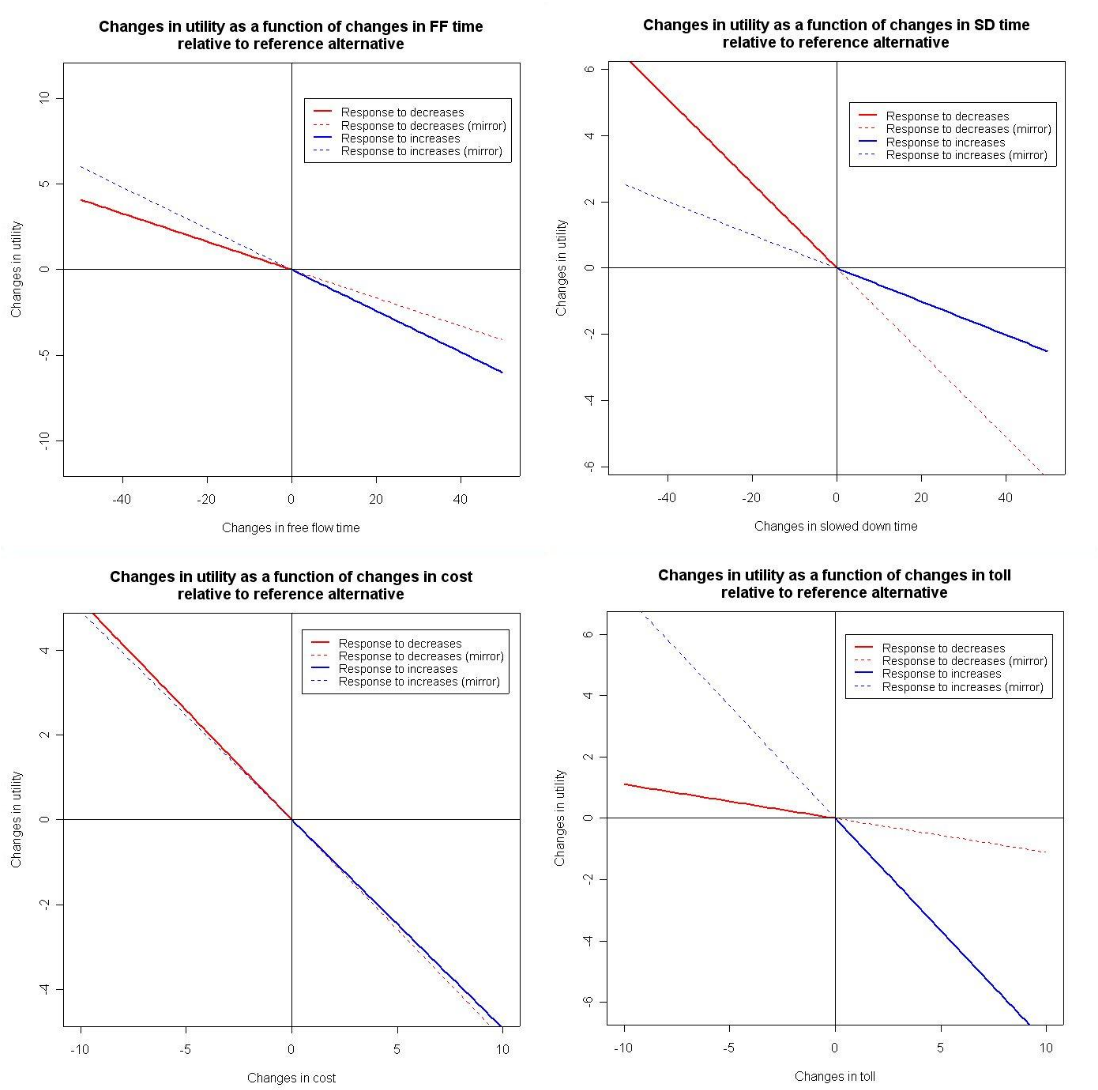

Figure 2: Evidence of asymmetrical response to changes in attributes for non-commuters

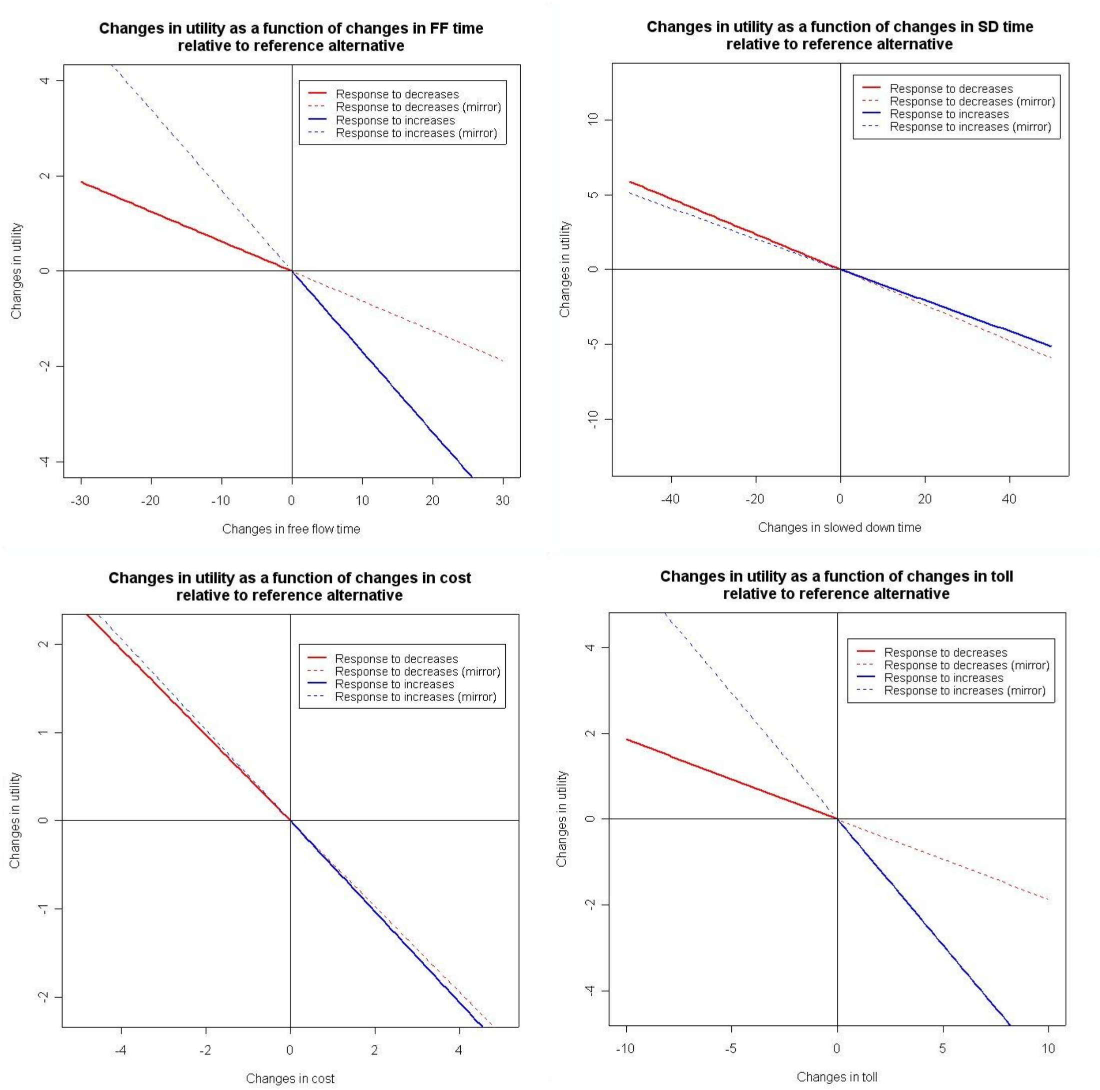

Figure 3: Evidence of asymmetrical response to changes in attributes for commuters

Table 7: Asymptotic *t*-ratios for differences between separate travel time and travel cost coefficients (panel specification for asymmetrical models)

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

Table 8: Ratios between parameter estimates for separate travel time and travel cost components (panel specification for asymmetrical models)

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

Table 9: Willingness to pay indicators for asymmetrical models using panel specification

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

Table 10: Willingness to accept increases in travel time in return for decreases in travel cost or road tolls for base model (min/AUD) based on symmetrical models using panel specification

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

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

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