THE UNIVERSITY OF MELBOURNE

FACULTY OF BUSINESS & ECONOMICS

Melbourne Institute Working Paper Series

Working Paper No. 16/15

Loss Aversion, Reference Dependence and Diminishing Sensitivity in Choice Experiments

Anthony Scott and Julia Witt

MELBOURNE INSTITUTE®
of Applied Economic and Social Research

Loss Aversion, Reference Dependence and Diminishing Sensitivity in Choice Experiments*

Anthony Scott[†] and Julia Witt[‡]
[†] Melbourne Institute of Applied Economic and Social Research,
The University of Melbourne
[‡] Department of Economics, University of Manitoba

Melbourne Institute Working Paper No. 16/15

ISSN 1328-4991 (Print)

ISSN 1447-5863 (Online)

ISBN 978-0-7340-4388-7

September 2015

* This research was funded from an ARC Linkage Grant (LP0669209) with the Department of Human Services (Victoria). Anthony Scott received funding from an NHMRC Principal Research Fellowship (628471). This paper reflects the views of the authors, who have no conflicts of interest. For correspondence, email <Julia.Witt@umanitoba.ca>.

Melbourne Institute of Applied Economic and Social Research
The University of Melbourne
Victoria 3010 Australia
***Telephone* (03) 8344 2100**
***Fax* (03) 8344 2111**
***Email* melb-inst@unimelb.edu.au**
***WWW Address* http://www.melbourneinstitute.com**

Abstract

In the discrete choice experiment literature, it has been argued that the choice sets from which respondents choose should include an unforced choice because this is more realistic and accounts for status quo bias. However, we propose a much stronger set of arguments for preferring to use unforced choices where relevant. These relate to the concepts of loss aversion, reference dependence and diminishing sensitivity from prospect theory. We use data from a discrete choice experiment of different types of jobs for nurses, where the introduction of a third alternative, representing the respondent's current job, changes the reference point, which is different for each respondent. The increased salience of the reference point, in turn, changes the size of any losses or gains when comparing Job A or Job B with their current situation, and since losses are valued more than gains, this affects the marginal utility of each attribute. This has implications for policy conclusions based on willingness to pay. Including an unforced choice is necessary (when appropriate) not only for the purposes of 'realism', but also because different marginal utilities are produced due to loss aversion, reference dependence and diminishing sensitivity.

JEL classification: I11, J24, J32, D80, C99

Keywords: Discrete choice experiments, loss aversion, reference dependence, diminishing sensitivity, health workforce

1. Introduction

Choice experiments are designed to elicit preferences based on theories of how respondents make choices, and these valuations are used in many different applications. In some contexts respondents who are asked to decide between two or more hypothetical goods in a choice experiment already have a current option/situation or a status quo or can delay making a choice and so do not have to choose. A range of arguments have been made to explicitly include an alternative in the choice set that represents the status quo or current situation or opt out (Lancsar and Louviere, 2008; Rose and Hess, 2010). These arguments include an increase in realism that recognises that individuals can postpone choice or decide not to choose at all, an ability to make more accurate predictions of demand and market shares, an increase in the external validity of welfare estimates, and an improvement in statistical efficiency.

The aim of this paper is to further investigate the reasons for, and impact of, the inclusion of a status quo alternative in a DCE. We contribute to the literature by explicitly distinguishing between and testing the theories of loss aversion, diminishing sensitivity and reference dependence using qualitative attributes, which are common in discrete choice experiments in health economics. Our analysis specifically includes the reference point to test whether respondents value changes differently when they start from different positions. We do this in the context of a DCE for preferences for job characteristics answered by nurses. Results of different specifications that differentially capture the three concepts of loss aversion, diminishing sensitivity and reference dependence are compared.

In applications of DCEs in health economics, the potential importance of the status quo was first noted by Salkeld *et al.* (2000) and recommended in a review by Lancsar and Louviere (2008). In many applications of DCEs in health economics the provision of a status quo alternative is a recent development and is becoming common practice (e.g. Fiebig *et al*., 2011; Rao *et al*., 2012). In a forced choice, the status quo is not explicit or salient. Respondents may still use their current situation and experience when making choices. Experience with the good being valued is a particular issue as for some stated preference tasks respondents may have little experience of the good or service and their preferences are being formed as they complete the task (Shiell *et al*., 2000). However, in a forced choice it is more difficult for the researcher to take this into account when analysing the data. For example, one can use interaction terms with observed characteristics that reflect respondents' current situation or existing experience. Previous studies in health have shown that the current situation influences the marginal utilities of attributes (eg Scott, 2001; Scott *et al*., 2003), providing some evidence of the impact of reference dependent preferences and experience on the marginal utilities of attributes.

From the perspective of utility theory, using a 'forced' choice in a DCE where only the new alternatives are presented should lead to the same marginal utilities as when including an alternative that includes the status quo or current situation (hereafter referred to as an 'unforced' choice). Economic theory assumes an attribute of a good or service has an inherent value that does not vary with context and individuals have well-formed preferences. It is now well established, however, that including a status quo option also captures strong preferences for the status quo that are not a function of the attribute levels.

Status quo bias can be accommodated in variations of expected utility theory. Prospect Theory (Kahneman & Tversky, 1979) recognizes that reference points influence choices, and movements away from the reference point are evaluated in terms of gains and losses relative to this point. In a series of experiments, individuals were found to be more sensitive to losses than to gains when evaluating their options, and were generally risk-seeking when outcomes were losses, and risk-averse when outcomes were gains. This implies an *s*-shaped value function, where losses lead to larger reductions in value than equivalent sized gains. Thaler (1980) describes this phenomenon as an endowment effect. If individuals view losses as out-of-pocket costs, and gains as forgone opportunity costs, then losses will be weighted more heavily, and any change is evaluated relative to the individual's endowment. Samuelson and Zeckhauser (1988) document similar behaviour, which they call a "status quo bias". They cite a range of examples from observations and experiments that support that status quo biases are ubiquitous and significant, and that the bias increases with the number of choice alternatives. The design of their experiments, in fact, allows them to conclude that status quo bias is generally present, not just as a result of loss aversion (Samuelson and Zeckhauser, 1988).

In addition to loss aversion, there are a number of other reasons why respondents may prefer to choose the status quo alternative in choice experiments. First, there may be unobserved attributes that lead to a preference for the status quo. This may include unobserved attributes about the new alternatives or about the status quo (Salkeld *et al.*, 2000). This is essentially a model specification issue that can be minimised through careful piloting where only the most important attributes are included. Second, one may choose the status quo because of preference uncertainty or the difficulty of making such choices (Brazell *et al.*, 2006). Third, in stated preference choice tasks, the status quo may be chosen because respondents are not engaging with the choice task at all and rather than miss the question, they choose the status quo for all choices. These latter two explanations can be addressed by accounting for the effects of scale heterogeneity using a Generalised Multinomial Logit (GMNL) model (Fiebig *et al.*, 2010).

The issues of using an unforced choice and of modelling loss aversion have been examined in applications of DCEs to transport. Some studies have included a dual response, where respondents are presented with alternatives and asked to make a forced choice, and are also asked whether they would prefer the status quo in a second choice question (Brazell *et al.*, 2006; Dhar and Simonson, 2003; Rose and Hess, 2010). These studies have used different designs and orderings of the responses that depended on their context, and also focused on violations of the IIA assumption when an additional choice is added, rather than the effects on marginal utilities. This reflects a focus in the transport literature of predicting market shares. Rose and Hess (2010) examine dual responses and the effects on coefficients and find few differences between welfare estimates from forced and unforced choices.

There has been increasing interest in incorporating reference dependent model specifications that use pivot designs where attribute levels are increased or decreased by certain percentages around an individuals' reference levels. These can be used to model the asymmetric effects of losses and gains, and also whether the utility of losses and gains diminish with the distance from the reference point (Hess et al., 2008; Masiero and Hensher, 2010; Masiero and Rose, 2010; Rose and Masiero, 2010; Stathopoulos and Hess, 2012). In addition to transport applications, there have been some applications in marketing (Hardie *et al.*, 1993) and in health (Salkeld *et al.*, 2000) that incorporate reference points in choice experiments and these have found evidence of loss aversion in the context of reference-dependent preferences.

One paper that is particularly relevant to our methodology is Masiero and Hensher (2010). They used a DCE of three transport choices in which they framed attribute levels as percentage changes from the current (reference) level, and then included the reference level as a choice option. Three specifications were tested: one where each attribute (time, cost, punctuality) was represented by one continuous variable; one where variables for all the attributes were split into increases and decreases relative to the reference point; and a third that split two attributes (cost and time) into increases and decreases as before, and allowed for a non-linearity in punctuality, which was split into two increase and two decrease levels (up to 2%, and 2% and up). This allowed them to test for loss aversion by comparing the coefficients of increases with those of decreases, and for the s-shape of the value function by comparing the coefficient of the smaller increase (decrease) with the coefficient of the larger increase (decrease). Their results support the existence of loss aversion and diminishing sensitivity.

One aspect of prospect theory they did not explicitly test is the importance of the reference point. While they framed their attributes in terms of gains and losses around respondents' current situation, they use percentage gains in their analyses, consequently treating equal-sized percentage changes equivalently, regardless of the actual reference level (or starting position) of respondents. Kahneman & Tversky (1979) recognize the importance of the starting point, suggesting that "…value should be treated as a function in two arguments: the asset position that serves as reference point, and the magnitude of the changes (positive or negative) from that reference point." (page 277).

2. Methods

The following four hypotheses are tested:

1) loss aversion is prevalent;

2) the reference point of each respondent matters;

3) there is diminishing sensitivity; and

4) including a status quo option changes the results and welfare estimates.

The data come from a DCE examining job preferences of nurses. The methods of the nurses' DCE are in Scott *et al*. (2015). Briefly, the DCE was completed by 990 nurses based in Victoria, Australia in 2008. Attributes included earnings, hours worked, public or private sector employment, autonomy, shift type, processes to deal with violence and bullying, and patient to nurse ratio. Nurses could choose to fill out a hard copy or online version, with 49% completing the survey online.

In the DCE, respondents were presented with a dual response question format, where the first response is a choice between two hypothetical alternatives (which job do you prefer) and the second is a choice between the same two alternatives (which job would you choose) but also includes the option 'stay at my current job' (Figure 1). The attribute levels for the third status quo alternatives were constructed after the DCE was administered using other questions from the survey that replicated the levels of each attribute.

In the forced choice, respondents are likely to be influenced by their current situation, but this is indirect and implicit and so the focus of the choice task is on the valuation of the hypothetical alternatives. Our income and hours attributes are pivoted around current levels by including a level of 'no change' with other levels plus or minus a certain percentage change. Though this increases the salience of their current reference point for those attributes compared to using levels of these attributes, pivoting was included because the range of hours and income in levels would be too great for those who worked part time. This may lead to a more conservative interpretation of our results since the status quo may influence respondents in the forced choice question, introducing some status quo bias into these as well.

With the exception of the pivoted levels for earnings and hours worked, the marginal utilities of other attributes in these models are 'averages' of the marginal utilities of gains and losses. We start with the usual framework that alternatives can be represented by a utility function, for respondent *n* and alternative *j*:

$$U_{nj} = \boldsymbol{\beta}'\boldsymbol{X}_{nj} + \boldsymbol{\varepsilon}_{nj}$$

where $\boldsymbol{V}_{nj} = \boldsymbol{\beta}'\boldsymbol{X}_{nj}$ is the systematic part of the utility function, and $\boldsymbol{\varepsilon}_{nj}$ a random error term that is IID. Attribute levels for categorical variables are effects coded, and we use a GMNL model to estimate the mean and standard deviation of $\boldsymbol{\beta}$ to allow for preference and scale heterogeneity. Each alternative (j = 1,2,3) in a choice set can be written as follows:

Model 1:

$$\begin{aligned}\boldsymbol{V}_{n(\mathrm{alt}j)} = {} & ASC_{\mathrm{alt}j} + \beta_{\mathrm{earn}}\mathrm{EARN}_j + \beta_{\mathrm{hrs1}}\mathrm{HRS1}_j + \beta_{\mathrm{hrs2}}\mathrm{HRS2}_j + \beta_{\mathrm{emp1}}\mathrm{EMP1}_j + \beta_{\mathrm{aut1}}\mathrm{AUT1}_j \\ & + \beta_{\mathrm{aut2}}\mathrm{AUT2}_j + \beta_{\mathrm{sft1}}\mathrm{SFT1}_j + \beta_{\mathrm{sft2}}\mathrm{SFT2}_j + \beta_{\mathrm{prc1}}\mathrm{PRC1}_j + \beta_{\mathrm{prc2}}\mathrm{PRC2}_j \\ & + \beta_{\mathrm{pat1}}\mathrm{PAT1}_j + \beta_{\mathrm{pat2}}\mathrm{PAT2}_j\end{aligned}$$

where the X's are the attribute levels in the DCE, and ASC is the alternative specific constant. There are three alternatives per choice set, and alternative three is always the status quo. This is the usual utility model which accounts for 'general' status quo bias through the inclusion of the alternative specific constant term for the status quo alternative.

We change this model to explicitly account for loss aversion and diminishing sensitivity by redefining attribute levels in terms of deviations from the status quo attribute level in alternative 3 rather than the effects coded levels as they appear in the DCE. The first specification (Model 2) considers the absolute level change for each attribute from the status quo.

Model 2:

$$\boldsymbol{V}_{n(\mathrm{alt}j)} = ASC_{\mathrm{alt}j} + \beta_{\mathrm{earn}}\mathrm{EARN}_j + \beta_{\mathrm{hrsL1}}\mathrm{hrsL1}_j + \beta_{\mathrm{hrsG1}}\mathrm{hrsG1}_j + \beta_{\mathrm{empL1}}\mathrm{empL1}_j + \beta_{\mathrm{empG1}}\mathrm{empG1}_j + \beta_{\mathrm{autL2}}\mathrm{autL2}_j + \beta_{\mathrm{autL1}}\mathrm{autL1}_j + \beta_{\mathrm{autG1}}\mathrm{autG1}_j + \beta_{\mathrm{autG2}}\mathrm{autG2}_j + \beta_{\mathrm{sftL2}}\mathrm{sftL2}_j + \beta_{\mathrm{sftL1}}\mathrm{sftL1}_j + \beta_{\mathrm{sftG1}}\mathrm{sftG1}_j + \beta_{\mathrm{sftG2}}\mathrm{sftG2}_j + \beta_{\mathrm{prcL2}}\mathrm{prcL2}_j + \beta_{\mathrm{prcL1}}\mathrm{prcL1}_j + \beta_{\mathrm{prcG1}}\mathrm{prcG1}_j + \beta_{\mathrm{prcG2}}\mathrm{prcG2}_j + \beta_{\mathrm{patL2}}\mathrm{patL2}_j + \beta_{\mathrm{patL1}}\mathrm{patL1}_j + \beta_{\mathrm{patG1}}\mathrm{patG1}_j + \beta_{\mathrm{patG2}}\mathrm{patG2}_j$$

where the *X*'s are defined as gains "G" and losses "L" of one (L1 and G1) or two (L2 or G2) levels from the status quo for each attribute level for the three alternatives. This is referred to as the 'linear gains/losses model'. It is linear because a change in 1 level does not depend on the level that the respondent starts at – the same coefficient estimates the preference for this change regardless of whether the respondent starts at a high or medium level. The model does, however, account for i) diminishing sensitivity where there may be a difference in utility between a change in 1 or 2 levels, and ii) loss aversion where changes are defined as a gain (G) or loss (L). Table 1 shows the distribution of gains or losses (of any size) relative to the status quo for each attribute and shows that for most attributes the distribution is symmetric with equal proportions of gains and losses appearing in the experiment.

The second (Model 3) considers the relative change, that is, the magnitude of the change and the reference point defined by the status quo levels. The following shows the full model that accounts for loss aversion, reference point bias and diminishing sensitivity.

Model 3:

$$
\begin{aligned}
\boldsymbol{V}_{n(\text{alt}j)} = {} & ASC_{\text{alt}j} + \beta_{\text{earn}}\text{EARN}_j + \beta_{\text{hrsL1}}\text{hrsL1}_j + \beta_{\text{hrsG1}}\text{hrsG1}_j + \beta_{\text{empL12}}\text{empL12}_j \\
& + \beta_{\text{empG11}}\text{empG11}_j + \beta_{\text{autL23}}\text{autL23}_j + \beta_{\text{autL13}}\text{autL13}_j + \beta_{\text{autL12}}\text{autL12}_j \\
& + \beta_{\text{autG11}}\text{autG11}_j + \beta_{\text{autG12}}\text{autG12}_j + \beta_{\text{autG21}}\text{autG21}_j + \beta_{\text{sftL23}}\text{sftL23}_j \\
& + \beta_{\text{sftL13}}\text{sftL13}_j + \beta_{\text{sftL12}}\text{sftL12}_j + \beta_{\text{sftG11}}\text{sftG11}_j + \beta_{\text{sftG12}}\text{sftG12}_j \\
& + \beta_{\text{sftG21}}\text{sftG21}_j + \beta_{\text{prcL23}}\text{prcL23}_j + \beta_{\text{prcL13}}\text{prcL13}_j + \beta_{\text{prcL12}}\text{prcL12}_j \\
& + \beta_{\text{prcG11}}\text{prcG11}_j + \beta_{\text{prcG12}}\text{prcG12}_j + \beta_{\text{prcG21}}\text{prcG21}_j + \beta_{\text{patL23}}\text{patL23}_j \\
& + \beta_{\text{patL13}}\text{patL13}_j + \beta_{\text{patL12}}\text{patL12}_j + \beta_{\text{patG11}}\text{patG11}_j + \beta_{\text{patG12}}\text{patG12}_j \\
& + \beta_{\text{patG21}}\text{patG21}_j
\end{aligned}
$$

where the *X*'s are the changes from the status quo for each attribute level in the three alternatives, but are stratified by starting point. The variable names and coefficient subscripts indicate the direction of change and the starting point; for example, "L23" means a loss of 2 levels, starting at level 3; "G12" means a gain of 1 level, starting at level 2. This is referred to as the 'non-linear gains/losses model'. It enables us to examine the marginal utility of all possible changes from any reference point. Table 2 shows the number of observations in each level for the non-linear model. The number corresponds to the number of times that particular scenario (for example, a loss of 2 levels in autonomy from reference level 3, or autL23) occurs in the dataset. Note that alternative 3 is always the reference category (the status quo), so the frequencies refer to the number of occurrences in alternatives 1 and 2.

We estimate Model 1 to obtain the usual DCE results, using the status quo alternative as a third option. Finally, for comparison, we estimate Model 1 using the forced choice data with only two alternatives, which does not account for status quo bias in any way. We call this Model 1A. This will allow us to compare the effect of including a third alternative in the questionnaire, which we hypothesize to significantly affect the results.

In order to compare the results of these models, we calculate marginal rates of substitution (MRS), which is a common calculation from DCE data analysis results, and which provides us with a consistent basis for comparison across models. Since attribute levels are effects coded (Bech and Gyrd-Hansen, 2005) for all analyses (except *earnings*), each coefficient shows the absolute level of utility, rather than the utility for a marginal change. Effects coding removes the reference category of categorical variables from the constant terms so ASCs can be directly interpreted as a preference for A or B compared to the status quo. Therefore, calculating MRS requires recovering the reference category coefficient (which is coded as "-1") and subtracting this from each coefficient. This yields the marginal utility, and the MRS is then simply obtained by dividing by the *earnings* coefficient.

The marginal rate of substitution is calculated for each possible level change for all three specifications. There are fewer variables in models 1 and 2 since reference points are not explicit in these specifications, so we calculate all possible changes using the variable definitions from model 3. For model 1, this implies that the MRS of gains and losses are for the average respondent, and that gains and losses are symmetric. For specification 2, this implies a step-like function where a specific change (for example, a loss of 1 level or a gain of 1 level) is the same regardless of the reference category. To illustrate, the following equations show the MRS calculation for a gain of 1 level in autonomy, using level 1 as the reference point (i.e., a gain of one level from "poor" autonomy (level 1, reference point) to "adequate" autonomy (level 2)). Note that, for model 1, "poor" autonomy is the omitted level, and so this coefficient has to be recovered in the calculation. For models 2 and 3, the omitted level is always "no change from reference point", and this coefficient is subtracted from the relevant coefficient to measure the entire impact of the change.

Model 1: $$MRS_{\text{aut1 to aut2}} = \frac{\beta_{\text{aut1}} - (-\beta_{\text{aut1}} - \beta_{\text{aut2}})}{\beta_{\text{earn}}}$$

Model 2: $$MRS_{\text{autG1}} = \frac{\beta_{\text{autG1}} - (-\beta_{\text{autL2}} - \beta_{\text{autL1}} - \beta_{\text{autG1}} - \beta_{\text{autG2}})}{\beta_{\text{earn}}}$$

Model 3: $$MRS_{\text{autG11}} = \frac{\beta_{\text{autG11}} - (-\beta_{\text{autL23}} - \beta_{\text{autL13}} - \beta_{\text{autL12}} - \beta_{\text{autG11}} - \beta_{\text{autG12}} - \beta_{\text{autG21}})}{\beta_{\text{earn}}}$$

We also compare our unforced choice results to our forced choice results, and use the responses to the A/B question in the DCE to calculate the MRS as we did for model 1.

All models are estimated using the GMNL estimated in NLOGIT 5. The GMNL model controls for uncertainty about preferences and choice complexity by accounting for scale heterogeneity (Fiebig *et al.*, 2010). As explanations for status quo bias, preference uncertainty and choice complexity that are captured by scale are therefore accounted for when using GMNL.

3. Results

The choice shares for the forced choice and unforced choice and the transitions between the two types of response are described in Table 3. This provides information on the impact of the status quo on choice shares. Of the 2,643 who choose job A in the forced choice, only 29.4% choose job A in the unforced choice with 69.6% switching to the status quo. Similar proportions switch to the status quo from job B. Of the 831 who provided no response at all in the forced choice, 39.2% choose the status quo in the unforced choice.

Table 4 shows the means and standard deviations of the parameters for each model (1 to 3). The unforced choice model (Model 1) has large and significant alternative specific constants, which suggest a sizeable status quo bias not picked up by the job attributes included in our DCE. The *earnings* means are similar in magnitude across all models. The *hours* means are larger in model 3 than in models 1 and 2, both for gains and losses. Model 1 is not directly comparable to models 2 and 3 for any other means since these are not calculated in terms of gains and losses from a reference point. Model 1 shows the 'average' marginal utility across losses and gains. The means of model 3 show that the (dis)utility of equal sized gains and losses differ depending on the reference category. For example for autonomy, a loss of 1 level (L1) in model 2 does not account for the starting point of the loss. It gives an 'average' value of the loss of one level. However, in model 3, a loss of one level from Level 3 (L13) is valued less than a loss of one level from level 2 (L12). Model 2 assumes that the G1 and L1 means are equivalent regardless of the reference category, but model 3 shows that this is not in fact true.

Figures 2a to 2d illustrate the coefficient means for 4 attributes (*autonomy*, *shift*, *process*, *patient ratio*) from the 3 models for changes (gains and losses) of one level, using the unforced choice data. These are adjusted for the effects-coded reference category (i.e. the base category "-1"), and thus show the marginal utility of that particular gain/loss with respect to "no change". Since all attributes have 3 levels, the changes shown on the x-axis are (from left to right) a loss of one from level 3 to level 2; a loss of one from level 2 to level 1; no change (normalized to 0 by removing the base category); a gain of one from level 1 to level 2; and a gain of one from level 2 to level 3. In the symmetric model (Model 1), gains and losses are equivalent but opposite in sign. In the linear G/L model (Model 2), these are straight lines in either direction from the origin (no change) because not including the reference point assumes equal sized changes are equivalent. In the non-linear G/L model (Model 3), this is not restricted to be either symmetric or linear from the origin, and so shows how marginal utilities change depending on the reference level of gain or loss.

The first three hypotheses (loss aversion, reference dependence and diminishing sensitivity) can be formally tested with likelihood ratio (LR) tests since the three models are nested. We tested the hypotheses by restricting coefficients separately for each attribute and level. Tables 5 to 7 show the results for loss aversion, reference dependence and diminishing sensitivity, respectively. Not all hypotheses were testable with each specification: loss aversion can be tested with models 2 and 3, reference dependence with model 3, and diminishing sensitivity with models 2 and 3.

The results show that most of the null hypotheses that the coefficients are equivalent can be rejected. Note that the null hypothesis of coefficient equivalence does not automatically support our hypotheses of loss aversion and diminishing sensitivity. Rejecting H_0 rejects that the coefficients are equal, but in order for loss aversion to be present, the absolute value of losses must be larger than the absolute value of gains. Model 2 exhibits loss aversion for all attributes, except employer type, while model 3 exhibits loss aversion in 8 out of 14 cases, and for 2 cases the null hypothesis that the coefficients are equivalent could not be rejected (Table 5). In order for diminishing sensitivity to be present, the absolute value of the sum of the coefficients representing a one-level change must be larger than the two-level change coefficient. This is not the case for most of our coefficients, and our results appear to favour a hypothesis of increasing sensitivity. We do, however, consistently reject the hypothesis that the larger losses / gains are simply equal to the sum of smaller losses / gains.

Table 8 shows the means and standard deviations of the parameters for model 1 as a forced choice model (model 1A) compared to Model 1. The status quo was not completely defined for some respondents, and so we used only observations that were in our unforced choice sample to estimate the forced choice results. The mean of the earnings coefficient is over 10 times larger in the forced choice model than in the unforced choice models, and other attributes means are also different between these models. This has significant implications for WTP calculations, discussed below.

Table 9 shows marginal rates of substitution for all models, and these are reported as percent of average annual income. Changes in the number of hours worked yields a negative MRS for gains and losses in all models, suggesting that, on average, nurses do not want to change the number of hours they work. The larger means reported for model 3 in Table 4 are partially mediated by the larger coefficient on *earnings*, thus yielding similar MRS for *Hours* L1 and G1. Models 2 and 3 suggest a slight preference for changing employer type, regardless of which employer nurses currently work for (though there is a preference for public). Model 1 cannot distinguish between these. The remaining MRS of models 2 and 3 generally show that losses require larger compensation than gains. Model 3 further suggests the presence of non-linearities is driven by reference points. Model 1 suggests similar non-linearities, although gains and losses are treated as symmetric.

The most striking difference between the forced choice and the unforced choice models is the magnitude of the marginal rates of substitution: they are substantially smaller for model 1A. This is the result of the large earnings coefficient that was estimated for model 1A and suggests that respondents are very sensitive to even small changes in income. It implies that respondents would accept changes in attribute levels for changes in income that do not exceed 2%. The unforced choice models paint a vastly different picture: income compensations for changes are much higher, up to nearly 50% of annual income.

Since MRS is preference-based, there is no formal test to identify whether model 1 or model 1A better approximates true willingness to pay. However, there are clues in current compensation rates that are indicative that willingness to pay is closer to the amounts suggested by model 1 than by 1A. Currently penalty rates and shift loadings of a registered nurse are approximately 23% of weekly pay (ANMF, 2015); the average cost of a compensation claim due to workplace bullying was $41,700 (71.3% of average income) in 2007/08 (Safe Work Australia); and the salary difference between a Registered Nurse at a Grade 2 level in year 1 (little autonomy at entry level) compared to year 10 (more autonomy and responsibility with years of experience) is approximately 32% (DHHS). While these do not correspond directly to the level changes in our DCE, nor do they address all attributes, they do suggest salary changes for changes in working conditions closer in magnitude to the MRS of the unforced choice models. The changes in annual salary implied by model 1A are likely too little to adequately compensate for changes. We therefore use this as evidence to support our hypothesis that the unforced choice model better estimates true WTP.

4. Discussion

When presented with a choice, people prefer what they know or own even if the attributes of the new alternative are better (Kahneman and Tversky, 1979; Samuelson and Zeckhauser, 1988; Thaler, 1980; Tversky and Kahneman, 1991). This has been called the endowment effect, reference dependence, reference point bias, status quo bias, and loss aversion. This has been found across many decision making contexts in experimental and non-experimental studies, and is cited as the reason for the empirical difference between measures of willingness to pay and willingness to accept.

We tested theories of loss aversion, diminishing sensitivity and reference dependence in a series of analyses by constructing and comparing 3 specifications that differentially incorporate these theories. Our non-linear model (model 3) embodies all 3 theories. Our results generally support loss aversion and reference dependence, though not for all restrictions across all specifications. In contrast to Masiero & Hensher (2010), we found only weak support for diminishing sensitivity, where larger changes would lead to smaller changes in value compared to an equal-sized set of small changes. We did, however, find support for increasing sensitivity: larger changes mostly led to larger changes in value than an equivalent number of small changes, implying that respondents in our DCE are more sensitive to changes when these move them further away from their reference point. Our results are in line with the previous literature in the sense that larger changes are not simply the sum of equal-sized smaller changes.

Our results have important policy implications. Discrete choice experiments are frequently used to calculate willingness-to-pay (or willingness-to-accept) for certain attributes. Our results illustrate the sensitivity of WTP (or MRS) to the parameters that are used to calculate it. For instance, model 1 would suggest that switching a nurse from 'weekdays only' shifts to 'fixed' shifts would require compensation equivalent to 8.7% of average income. Average income in our sample is approximately A$58,425, which translates into an annual salary increase of around A$5,100. However, using the MRS calculated from model 3, nurses whose status quo is a 'weekdays only' shift would actually require compensation of 29% of income, or approximately A$16,950 per year, to switch to a 'fixed' shift. Using the parameters from model 2 puts this value at 14.8%, or approximately

A$8,650 per year. These differences are economically large. Compensation of A$5,100 would not compensate nurses adequately for switching to a ‘fixed’ shift, and if such a move were voluntary, would likely lead to very low uptake. An incentive of A$5,100 may even be counterproductive: if the compensation is low, then nurses already working less desirable shifts (in this case rotating shifts) will be the ones most likely to switch to fixed shifts, possibly creating staffing shortages for rotating shifts.

A limitation of our study is that our attribute levels are mostly qualitative, and are consequently more difficult to interpret. Some attributes are less complicated than others: all respondents would prefer very good autonomy to adequate autonomy, and adequate autonomy to poor autonomy. However, not all respondents may prefer a fixed shift to a rotating shift, and so this challenges what changes we interpret as a “loss” or a “gain”. Our DCE responses also showed that respondents preferred a change in employer type; regardless of employer type, switching was always preferred. However, the reality is that many DCEs, particularly in Health Economics, use qualitative attributes, and so it is important to analyse the theories in the context of such attributes. Moreover, all three specifications almost always yielded the same sign for changes, and so it was straightforward to assign these as a gain or a loss, though this would not always necessarily be the case.

There are implications for the future analysis of DCEs. It seems clear that, in the context presented in this paper, accounting for loss aversion and reference dependence for specific attributes, and general status quo bias through the inclusion of a third status quo alternative, leads to quite different estimates of marginal utilities and welfare estimates. Researchers should explore these issues in other decision making contexts.

5. References

Alfnes F, Guttormsen A, Steine G, Kolstad K, 2006. Consumers' Willingness to Pay for the Color of Salmon: A Choice Experiment with Real Economic Incentives. *American Journal of Agricultural Economics* 88(4): 1050-1061.

Aristides M, Weston A, FitsGerald P, Le Reun C, Maniadakis N. 2004. Patient Preference and Willingness-to-Pay for Humalog Mix25 Relative to Humulin 30/70: A Multicountry Application of a Discrete Choice Experiment. *Value in Health* 7(4): 442-454.

Australian Nursing and Midwifery Federation (ANMF), "Nurses, midwives will act if penalty rates are cut", available at: anmf.org.au, March 3, 2015.

Bech M, Gyrd-Hansen D. 2005. Effects coding in discrete choice experiments. *Health Economics* 14(10): 1079-1083.

Brazell J, Diener C, Karniouchina E, Moore W, Severin V, Uldry P. 2006. The no-choice option and dual response choice designs. *Marketing Letters* 17(4): 255-268.

Department of Health and Human Services (DHHS), 2007. Nurses Multiple Employer Agreement 2007 - 2011, available at: www.health.vic.gov.au

Dhar R, Simonson I. 2003. The Effect of Forced Choice on Choice. *Journal of Marketing Research* 40(2): 146-160.

Fiebig D, Keane M, Louviere J, Wasi N. 2010. The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity. *Marketing Science* 29(3): 393-421.

Fiebig D, Knox S, Viney R, Haas M, Street D. 2011. Preferences for new and existing contraceptive products. *Health Economics* 20(S1); 35-52.

Hess S, Rose J, Hensher D. 2008. Asymmetric preference formation in willingness to pay estimates in discrete choice models. *Transportation Research Part E: Logistics and Transportation Review* 44(5): 847-863.

Kahneman D, Tversky A. 1979. Prospect theory: an analysis of decision making under risk. *Econometrica* 47: 263-291.

Lancsar E, Louviere J. 2008. Conducting Discrete Choice Experiments to Inform Healthcare Decision Making. *PharmacoEconomics* 26(8): 661-677.

Masiero L, Hensher D. 2010. Analyzing loss aversion and diminishing sensitivity in a freight transport stated choice experiment. *Transportation Research Part A: Policy and Practice* 44(5): 349-358.

Masiero L, Rose J. 2010, The role of the reference alternative in the specification of asymmetric discrete choice models. 10th Swiss Transport Research Conference (STRC), September 2010, Ascona.

Potoglou D, Kanaroglou P. 2007. Household demand and willingness to pay for clean vehicles. *Transportation Research Part D: Transport and Environment* 12(4): 264-274.

Rao K, Shroff Z, Ramani S, Khandpur N, Murthy S, Hazarika I, Choksi M, Ryan M, Berman P, Vujicic M. 2012. How to Attract Health Workers to Rural Areas? Findings from a Discrete Choice Experiment from India, HNP Discussion Paper, World Bank, Washington DC.

Rose J, Hess S. 2010. Dual-Response Choices in Pivoted Stated Choice Experiments. *Transportation Research Record: Journal of the Transportation Research Board* 2135: 25-33.

Rose J, Masiero L. 2010. A Comparison of the Impacts of Aspects of Prospect Theory on WTP/WTA Estimated in Preference and WTP/WTA Space. *European Journal of Transport Infrastructure Research* 10(4): 330-346.

Safe Work Australia, Submission 74, available at: www.safeworkaustralia.gov.au

Salkeld G, Ryan M, Short L. 2000. The veil of experience: do consumers prefer what they know best? *Health Economics* 9(3): 267-270.

Samuelson W, Zeckhauser R. 1988. Status quo bias in decision making. *Journal of Risk and Uncertainty* 1(1): 7-59.

Scott A, Witt J, Duffield C, Kalb G. 2015. What do nurses and midwives value about their job? Results from a discrete choice experiment. *Journal of Health Services Research and Policy* 20(1): 31-38.

Scott A, Witt J, Humphreys J, Joyce C, Kalb G, Jeon S, McGrail M. 2013. Getting doctors into the bush: General Practitioners' preferences for rural location. *Social Science and Medicine* 96: 33-44.

Shiell A, Seymour J, Hawe P, Cameron S. 2000. Are preferences over health states complete? *Health Economics* 9(1): 47-55.

Stathopoulos A, Hess S. 2012. Revisiting reference point formation, gains–losses asymmetry and non-linear sensitivities with an emphasis on attribute specific treatment. *Transportation Research Part A: Policy and Practice* 46(10): 1673-1689.

Thaler R. 1980. Toward a Positive Theory of Consumer Choice. *Journal of Economic Behavior and Organization* 1(1): 39-60.

Tversky A, Kahneman D. 1991. Loss Aversion in Riskless Choice: A Reference-Dependent Model. *Quarterly Journal of Economics* 106(4): 1039-1061.

6. Tables

Table 1: Percentage of gains and losses relative to the status quo for each attribute

	Job A			Job B		
	% gains	**% same**	**% losses**	**% gains**	**% same**	**% losses**
Employment	24.72	54.34	20.94	23.92	55.01	21.06
Autonomy	45.18	33.72	21.1	46.28	33.28	20.44
Shift	36.49	34.84	28.69	36.11	33.98	29.91
Processes	35.32	33.25	31.43	34.5	33.95	31.55
Patient ratio	13.2	34.29	52.52	12.45	33.46	54.1
Hours	34.41	34.37	31.12	33.85	30.13	36.01
Earnings	33.89	32.26	33.85	34.38	33.33	32.29

Table 2: Frequencies for each combination of Model 3

Level Change	Frequency
Hours L1: no change to 10% increase	2,095
Hours G1: no change to 10% decrease	2,082
Employer type L1: public to private	1,468
Employer type G1: private to public	1,302
Autonomy L23: very good to poor	880
Autonomy L13: very good to adequate	868
Autonomy L12: adequate to poor	908
Autonomy G11: poor to adequate	272
Autonomy G12: adequate to very good	884
Autonomy G21: poor to very good	270
Shift L23: weekdays only to rotating	577
Shift L13: weekdays only to fixed	576
Shift L12: fixed to rotating	651
Shift G11: rotating to fixed	860
Shift G12: fixed to weekdays only	556
Shift G21: rotating to weekdays only	744
Processes L23: very good to poor	590
Processes L13: very good to adequate	595
Processes L12: adequate to poor	896
Processes G11: poor to adequate	548
Processes G12: adequate to very good	928
Processes G21: poor to very good	541
Patient Ratio L23: 1:3 to 1:5	299
Patient Ratio L13: 1:3 to 1:4	288
Patient Ratio L12: 1:4 to 1:5	250
Patient Ratio G11: 1:5 to 1:4	1,487
Patient Ratio G12: 1:4 to 1:3	236
Patient Ratio G21: 1:5 to 1:3	1,521

Table 3: Transitions between the forced and unforced choices

			Unforced choice (A/B/SQ)			
		No Response	*A*	*B*	*SQ*	*Total*
Forced choice (A/B)	*No Response*	501 (60.3%)	2 (0.2%)	2 (0.2%)	326 (39.2%)	831 (100%)
	A	15 (0.6%)	776 (29.4%)	13 (0.5%)	1,839 (69.6%)	2,643 (100%)
	B	20 (0.4%)	28 (1.1%)	703 (28.5%)	1,725 (70.0%)	2,466 (100%)
	Total	526	806	718	3,890	5,940

Table 4: GMNL Results for Models 1, 2 and 3

Variable **(Change per Model 3)**	**Model 1** **Mean** **(SD)**	**Model 2** **Mean** **(SD)**	**Model 3** **Mean** **(SD)**
Earnings	0.08093***	0.08268***	0.09602***
Hours L1	-0.89467***	-0.93194***	-1.56833***
(10% increase)	(1.19260***)	(1.12368***)	(2.14523***)
Hours G1	0.08609	0.18954	0.43132***
(10% decrease)	(0.88535***)	(0.82129***)	(1.31594***)
Employer: Public	0.21282***		
	(0.60918***)		
Autonomy: Very good	0.81482***		
	(0.58543***)		
Autonomy: Adequate	0.28175***		
	(0.30333*)		
Shift: Rotating	-0.50392***		
	(0.84540***)		
Shift: Fixed	-0.10056		
	(0.48408***)		
Processes: Very good	0.68123***		
	(0.58562***)		
Processes: Adequate	0.21961***		
	(0.85712***)		
Patient ratio: 1 : 3	0.46916***		
	(0.86992***)		
Patient ratio: 1 : 4	0.02945		
	(0.62431***)		
Employment L1		-0.29315	-0.34040
(public to private)		(0.49253**)	(0.88093***)
Employment G1		0.60124***	0.77837***
(private to public)		(0.52966***)	(0.91742***)
Autonomy L2 / L23[a]		-2.76558***	-3.29396***
(L23: very good to poor)		(0.97041***)	(0.20371)
Autonomy L1 / L13		-0.92956***	-1.84098***
(L13: very good to adequate)		(0.21615)	(0.90044***)
Autonomy - / L12			-2.30819***
(L12: adequate to poor)			(0.38834)
Autonomy - / G11			2.86289***
(G11: poor to adequate)			(1.04905***)
Autonomy G1 / G12		0.97813***	0.16480
(G12: adequate to very good)		(0.52147***)	(1.26725***)
Autonomy G2 / G21		2.11447***	4.14672***
(G21: poor to very good)		(0.00283)	(0.74047*)
Shift L2 / L23		-2.51185***	-3.92644***
(L23: weekdays to rotating)		(0.90801***)	(0.63362)
Shift L1 / L13		-0.37582	-2.40870***
(L13: weekdays to fixed)		(1.14581***)	(0.1156)
Shift - / L12			0.74984
(L12: fixed to rotating)			(2.10101***)
Shift - / G11			1.54514***

(G11: rotating to fixed)			(0.65179**)
Shift G1 / G12		1.0166***	1.30021**
(G12: fixed to weekdays)		(0.12819)	(0.43564)
Shift G2 / G21		1.02551***	1.90734***
(G21: rotating to weekdays)		(0.87492***)	(0.83729***)
Processes L2 / L23		-1.89428***	-3.92515***
(L23: very good to poor)		(0.5092*)	(0.88307**)
Processes L1 / L13		-0.59857***	-0.75970
(L13: very good to adequate)		(0.5412***)	(0.67956**)
Processes - / L12			-1.68052***
(L12: adequate to poor)			(0.94801***)
Processes - / G11			2.08659***
(G11: poor to adequate)			(1.18589***)
Processes G1 / G12		0.66024***	0.44146
(G12: adequate to very good)		(0.73374***)	(0.77280***)
Processes G2 / G21		1.77471***	3.79036***
(G21: poor to very good)		(0.5489**)	(0.20047)
Patient ratio L2 / L23		-1.43379***	-2.59969***
(L23: 1:3 to 1:5)		(0.81951**)	(0.37594)
Patient ratio L1 / L13		-0.72839***	-1.47531*
(L13: 1:3 to 1:4)		(0.19066)	(0.51787)
Patient ratio - / L12			-0.38981
(L12: 1:4 to 1:5)			(0.22114)
Patient ratio - / G11			1.37107***
(G11: 1:5 to 1:4)			(0.09468)
Patient ratio G1 / G12		0.53498***	0.37121
(G12: 1:4 to 1:5)		(0.47986***)	(1.19750***)
Patient ratio G2 / G21		1.14216***	2.09423***
(G21: 1:5 to 1:3)		(0.91376***)	(1.44031***)
Constant A	-2.02891***	-1.65084***	-2.26799***
Constant B	-2.52012***	-2.10325***	-2.78701***
Tau	0.1284	0.46103***	0.86905***
Gamma	0	0.57691***	0.00005
Sigma	0.51838	0.51142	0.5185
BIC	4,102.036	4,129.182	4,177.625
AIC	3,939.1	3,857.7	3,809.6
N	3,081	3,081	3,081
Pseudo R^2	0.426094	0.443443	0.455273

[a] first abbreviation (L2) is for model 2; second (L23) is for model 3

Table 5: Hypothesis Testing: Loss Aversion, Model 2 and Model 3

Hypothesis	LR Test $\sim \chi^2_2$	Conclusion
MODEL 2		
$\beta_{\text{hrsL1}} + \beta_{\text{hrsG1}} = 0$	53.47	Reject H_0
$\beta_{\text{empL1}} + \beta_{\text{empG1}} = 0$	266.88	Reject H_0 but $\beta_{\text{empL1}} < \beta_{\text{empG1}}$
$\beta_{\text{autL1}} + \beta_{\text{autG1}} = 0$	9.60	Reject H_0
$\beta_{\text{autL2}} + \beta_{\text{autG2}} = 0$	20.29	Reject H_0
$\beta_{\text{sftL1}} + \beta_{\text{sftG1}} = 0$	24.63	Reject H_0
$\beta_{\text{sftL2}} + \beta_{\text{sftG2}} = 0$	144.67	Reject H_0
$\beta_{\text{prcL1}} + \beta_{\text{prcG1}} = 0$	71.89	Reject H_0
$\beta_{\text{prcL2}} + \beta_{\text{prcG2}} = 0$	202.76	Reject H_0
$\beta_{\text{patL1}} + \beta_{\text{patG1}} = 0$	26.51	Reject H_0
$\beta_{\text{patL2}} + \beta_{\text{patG2}} = 0$	198.58	Reject H_0
MODEL 3		
$\beta_{\text{hrsL1}} + \beta_{\text{hrsG1}} = 0$	294.88	Reject H_0
$\beta_{\text{empL1}} + \beta_{\text{empG1}} = 0$	273.70	Reject H_0 but $\beta_{\text{empL1}} < \beta_{\text{empG1}}$
$\beta_{\text{autL12}} + \beta_{\text{autG11}} = 0$	22.61	Reject H_0 but $\beta_{\text{autL12}} < \beta_{\text{autG11}}$
$\beta_{\text{autL13}} + \beta_{\text{autG12}} = 0$	15.58	Reject H_0
$\beta_{\text{autL23}} + \beta_{\text{autG21}} = 0$	18.31	Reject H_0 but $\beta_{\text{autL23}} < \beta_{\text{autG21}}$
$\beta_{\text{sftL12}} + \beta_{\text{sftG11}} = 0$	56.21	Reject H_0 but $\beta_{\text{sftL12}} < \beta_{\text{sftG11}}$
$\beta_{\text{sftL13}} + \beta_{\text{sftG12}} = 0$	29.07	Reject H_0
$\beta_{\text{sftL23}} + \beta_{\text{sftG21}} = 0$	318.59	Reject H_0
$\beta_{\text{prcL12}} + \beta_{\text{prcG11}} = 0$	31.80	Reject H_0 but $\beta_{\text{prcL12}} < \beta_{\text{prcG11}}$
$\beta_{\text{prcL13}} + \beta_{\text{prcG12}} = 0$	2.28	Do not reject H_0
$\beta_{\text{prcL23}} + \beta_{\text{prcG21}} = 0$	19.14	Reject H_0
$\beta_{\text{patL12}} + \beta_{\text{patG11}} = 0$	23.40	Reject H_0
$\beta_{\text{patL13}} + \beta_{\text{patG12}} = 0$	20.02	Reject H_0
$\beta_{\text{patL23}} + \beta_{\text{patG21}} = 0$	1.46	Do not reject H_0

Table 6: Hypothesis Testing: Reference Dependence, Model 3

Hypothesis	LR test ~ χ^2_2	Conclusion
MODEL 3		
$\beta_{\text{autL13}} = \beta_{\text{autL12}} = \beta_{\text{autL1}}$	26.64	Reject H_0
$\beta_{\text{autG11}} = \beta_{\text{autG12}} = \beta_{\text{autG1}}$	4.98	Reject H_0 (10%)
$\beta_{\text{sftL13}} = \beta_{\text{sftL12}} = \beta_{\text{sftL1}}$	22.29	Reject H_0
$\beta_{\text{sftG11}} = \beta_{\text{sftG12}} = \beta_{\text{sftG1}}$	31.06	Reject H_0
$\beta_{\text{prcL13}} = \beta_{\text{prcL12}} = \beta_{\text{prcL1}}$	2.74	Do not reject H_0
$\beta_{\text{prcG11}} = \beta_{\text{prcG12}} = \beta_{\text{prcG1}}$	5.50	Reject H_0 (10%)
$\beta_{\text{patL13}} = \beta_{\text{patL12}} = \beta_{\text{patL1}}$	13.11	Reject H_0
$\beta_{\text{patG11}} = \beta_{\text{patG12}} = \beta_{\text{patG1}}$	4.06	Do not reject H_0

Table 7: Hypothesis Testing: Diminishing Sensitivity, Model 2 and Model 3

Hypothesis	LR test ~ χ^2_2	Conclusion
MODEL 2		
$2 * \beta_{\text{autL1}} = \beta_{\text{autL2}}$	26.60	Reject H_0 but $2 * \beta_{\text{autL1}} > \beta_{\text{autL2}}$
$2 * \beta_{\text{autG1}} = \beta_{\text{autG2}}$	9.15	Reject H_0 but $2 * \beta_{\text{autG1}} < \beta_{\text{autG2}}$
$2 * \beta_{\text{sftL1}} = \beta_{\text{sftL2}}$	383.56	Reject H_0 but $2 * \beta_{\text{sftL1}} > \beta_{\text{sftL2}}$
$2 * \beta_{\text{sftG1}} = \beta_{\text{sftG2}}$	34.78	Reject H_0
$2 * \beta_{\text{prcL1}} = \beta_{\text{prcL2}}$	181.29	Reject H_0 but $2 * \beta_{\text{prcL1}} > \beta_{\text{prcL2}}$
$2 * \beta_{\text{prcG1}} = \beta_{\text{prcG2}}$	43.03	Reject H_0 but $2 * \beta_{\text{prcG1}} < \beta_{\text{prcG2}}$
$2 * \beta_{\text{patL1}} = \beta_{\text{patL2}}$	3.87	Do not reject H_0
$2 * \beta_{\text{patG1}} = \beta_{\text{patG2}}$	25.20	Reject H_0 but $2 * \beta_{\text{patG1}} < \beta_{\text{patG2}}$
MODEL 3		
$\beta_{\text{autL12}} + \beta_{\text{autL13}} = \beta_{\text{autL23}}$	17.93	Reject H_0
$\beta_{\text{autG11}} + \beta_{\text{autG12}} = \beta_{\text{autG21}}$	45.14	Reject H_0 but $\beta_{\text{autG11}} + \beta_{\text{autG12}} < \beta_{\text{autG21}}$
$\beta_{\text{sftL12}} + \beta_{\text{sftL13}} = \beta_{\text{sftL23}}$	55.99	Reject H_0 but $\beta_{\text{sftL12}} + \beta_{\text{sftL13}} > \beta_{\text{sftL23}}$
$\beta_{\text{sftG11}} + \beta_{\text{sftG12}} = \beta_{\text{sftG21}}$	57.92	Reject H_0
$\beta_{\text{prcL12}} + \beta_{\text{prcL13}} = \beta_{\text{prcL23}}$	19.84	Reject H_0 but $\beta_{\text{prcL12}} + \beta_{\text{prcL13}} > \beta_{\text{prcL23}}$
$\beta_{\text{prcG11}} + \beta_{\text{prcG12}} = \beta_{\text{prcG21}}$	226.25	Reject H_0 but $\beta_{\text{prcG11}} + \beta_{\text{prcG12}} < \beta_{\text{prcG21}}$
$\beta_{\text{patL12}} + \beta_{\text{patL13}} = \beta_{\text{patL23}}$	9.34	Reject H_0 but $\beta_{\text{patL12}} + \beta_{\text{patL13}} > \beta_{\text{patL23}}$
$\beta_{\text{patG11}} + \beta_{\text{patG12}} = \beta_{\text{patG21}}$	29.86	Reject H_0 but $\beta_{\text{patG11}} + \beta_{\text{patG12}} < \beta_{\text{patG21}}$

Table 8: Model 1, Forced Choice (1A) and Unforced Choice (1)

Variable	**Model 1A Mean (SD)**	**Model 1 Mean (SD)**
Earnings	0.90362***	0.08093***
Hours 10% increase	-0.69321***	-0.89467***
	(0.48918***)	(1.19260***)
Hours: 10% decrease	0.22674***	0.08609
	(0.28776)	(0.88535***)
Employer: Public	0.10940*	0.21282***
	(0.09120)	(0.60918***)
Autonomy: Very good	0.65747***	0.81482***
	(0.22582)	(0.58543***)
Autonomy: Adequate	0.19273**	0.28175***
	(0.02407)	(0.30333*)
Shift: Rotating	-0.45238***	-0.50392***
	(0.59371***)	(0.84540***)
Shift: Fixed	-0.36211***	-0.10056
	(0.76407***)	(0.48408***)
Processes: Very good	0.28649***	0.68123***
	(0.41297***)	(0.58562***)
Processes: Adequate	0.25796***	0.21961***
	(0.09512)	(0.85712***)
Patient ratio: 1 : 3	0.50529***	0.46916***
	(0.18841)	(0.86992***)
Patient ratio: 1 : 4	-0.20078*	0.02945
	(0.05770)	(0.62431***)
Constant A	0.23583***	-2.02891***
Constant B		-2.52012***
Tau	0.21515	0.1284
Gamma	1.0000	0
Sigma	0.51870	0.51838
BIC	3,286.825	4,102.036
AIC	3,130.0	3,939.1
N	3,081	3,081
Pseudo R^2	0.2793627	0.426094

Table 9: Marginal rates of substitution (MRS), % of income

Level Change	Model 1A	Model 1	Model 2	Model 3
Hours L1: no change to 10% increase	-1.3	-21.0	-20.3	-28.2
Hours G1: no change to 10% decrease	-0.3	-8.9	-6.7	-7.4
Employer type L1: public to private	-0.2	-5.3	0.2	1.0
Employer type G1: private to public	0.2	5.3	11.0	12.7
Autonomy L23: very good to poor	-1.7	-23.6	-40.7	-37.1
Autonomy L12: adequate to poor	-1.2	-17.0	-18.5	-26.8
Autonomy L13: very good to adequate	-0.5	-6.6	-18.5	-21.9
Autonomy G12: adequate to very good	0.5	6.6	4.5	-1.05
Autonomy G11: poor to adequate	1.2	17.0	4.5	27.1
Autonomy G21: poor to very good	1.7	23.6	18.3	40.4
Shift L23: weekdays only to rotating	-1.4	-13.7	-40.6	-49.6
Shift L13: weekdays only to fixed	-1.3	-8.7	-14.8	-33.8
Shift L12: fixed to rotating	-0.1	-5.0	-14.8	-0.9
Shift G11: rotating to fixed	0.1	5.0	2.1	7.4
Shift G12: fixed to weekdays only	1.3	8.7	2.1	4.9
Shift G21: rotating to weekdays only	1.4	13.7	2.2	11.2
Processes L23: very good to poor	-0.9	-19.5	-23.6	-41.4
Processes L12: adequate to poor	-0.8	-13.8	-7.9	-18.0
Processes L13: very good to adequate	-0.1	-5.7	-7.9	-8.4
Processes G12: adequate to very good	0.1	5.7	7.3	4.1
Processes G11: poor to adequate	0.8	13.8	7.3	21.2
Processes G21: poor to very good	0.9	19.5	20.8	39.0
Patient Ratio L23: 1:3 to 1:5	-0.9	-12.0	-23.2	-33.6
Patient Ratio L12: 1:4 to 1:5	-0.1	-6.5	-14.7	-10.6
Patient Ratio L13: 1:3 to 1:4	-0.8	-5.4	-14.7	-21.9
Patient Ratio G12: 1:4 to 1:3	0.8	5.4	0.6	-2.7
Patient Ratio G11: 1:5 to 1:4	0.1	6.5	0.6	7.7
Patient Ratio G21: 1:5 to 1:3	0.9	12.0	7.9	15.3

7. Figures

Figure 1: Example of a dual response choice experiment

Please read the following:

- You are asked to state which of the two jobs (A or B) is better.
- You are then asked which job you would choose, including the option of staying in your current job.
- Everything about the jobs you are comparing is the same, except for the characteristics shown below.

Please use the following table to answer questions 10 and 11:

	Job A	Job B
Change in earnings	15% Increase	No change
Change in hours worked	10% decrease	10% Increase
Type of employer	Public	Public
Autonomy	Poor	Very good
Shift type	Weekdays only	Weekdays only
Processes that deal with violence and bullying	Poor	Adequate
Number of patients cared for per nurse	3	5

10.	Which job do you think is better?	Job A ☐	Job B ☐	
11.	Which job would you choose?	Job A ☐	Job B ☐	Stay at my current job ☐

Figure 2: Coefficient comparison, models 1, 2 and 3 (1-level change)

Figure 2a: Autonomy

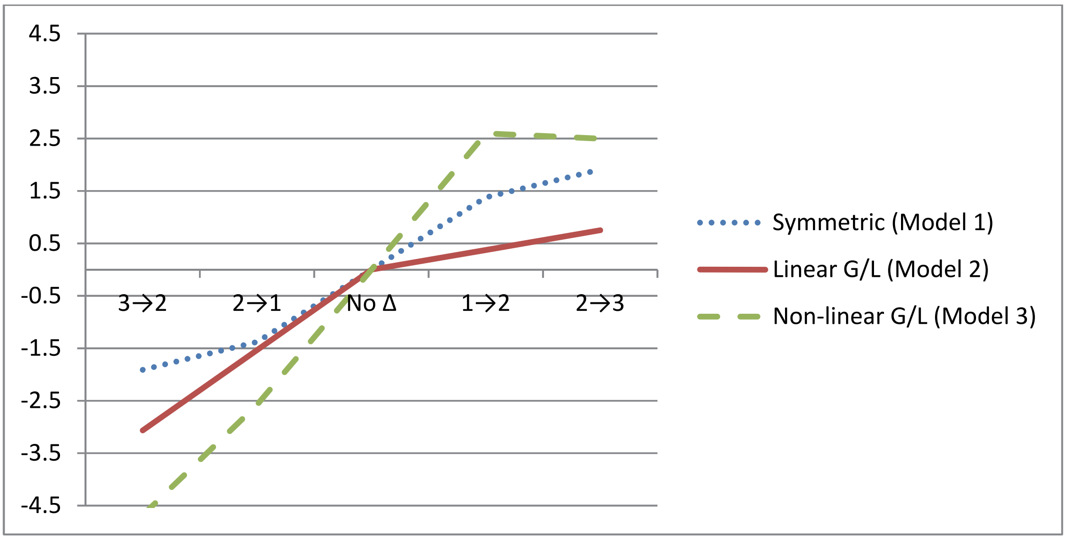

Figure 2b: Shift type

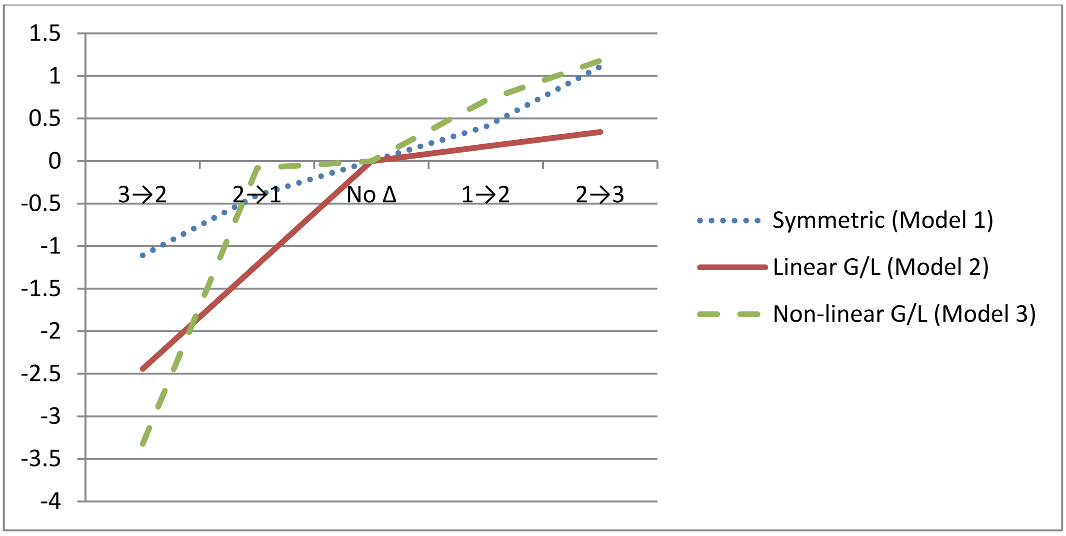

Figure 2c: Processes

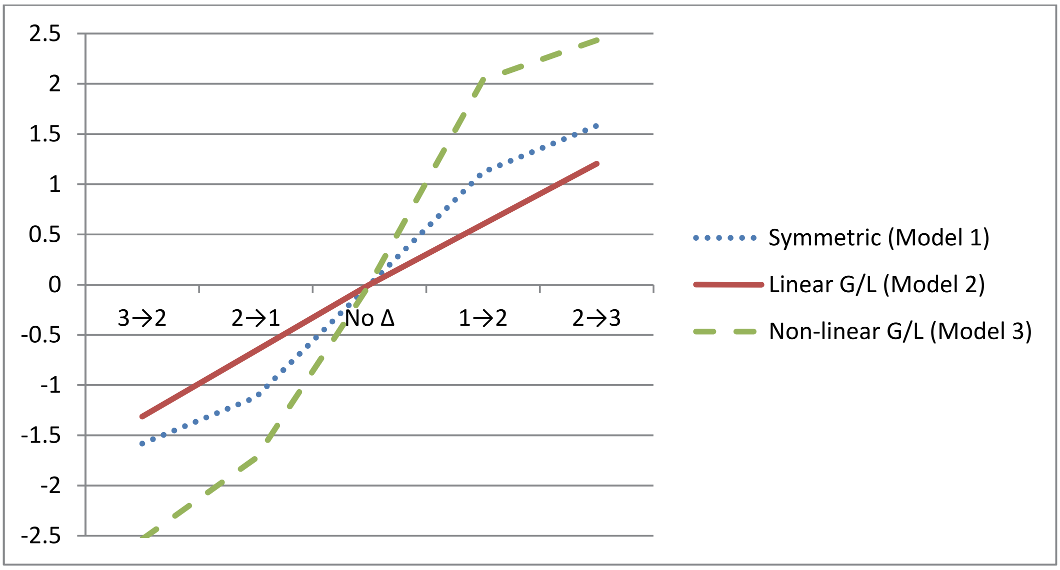

Figure 2d: Patient ratio