# HEDS Discussion Paper 06/06



**Published paper**
Ratcliffe J, Brazier J, Tsuchiya A, Symonds T, Brown M. Using DCE and ranking data to estimate cardinal values for health states for deriving a preference-based single index from the sexual quality of life questionnaire. Health Economics [in press].

ScHARR

SCHOOL OF HEALTH AND RELATED RESEARCH

The University of Sheffield

**ScHARR**
**School of Health and Related Research**

# Health Economics and Decision Science

**Discussion Paper Series**
**November 2006**

**Ref: 06/6**

## Estimation of a preference based single index from the sexual quality of life questionnaire (SQOL) using ordinal data.

Ratcliffe J[1], Brazier J[1], Tsuchiya A[1], Symonds T[2], Brown, M[2]

1. Health Economics and Decision Sciences, ScHARR, University of Sheffield
2. Worldwide Outcomes Research, Pfizer Global Pharmaceuticals, Pfizer Ltd

Corresponding Author:
Julie Ratcliffe
Health Economics and Decision Science
School of Health and Related Research
University of Sheffield
Regent Court, Sheffield, UK
S1 4DA
Email: j.ratcliffe@sheffield.ac.uk

**Abstract**

There is increasing interest in using ordinal methods to estimate cardinal values for health states to calculate quality adjusted life years. This paper reports the estimation of models of rank data and discrete choice experiment (DCE) data to derive a preference-based index from a condition specific measure relating to sexual health and to compare the results to values generated from time trade-off valuation (TTO). The DCE data were analysed using a random effects probit model and the DCE predicted values were re-scaled according to the highest and lowest predicted TTO values corresponding to the best and worst SQOL health states respectively. The Rank data were analysed using a rank ordered logit model and re-scaled using two alternative methods. Firstly, re-scaling the rank predicted values using identical methods to those employed for DCE and secondly, re-scaling the rank model coefficients by dividing each level coefficient by the coefficient relating to death. The study raises some important issues about the use of ordinal data to produce cardinal health state valuations.

## 1. Introduction

Health state values are usually obtained using cardinal methods such as standard gamble (SG), time trade-off (TTO) or visual analogue scaling (VAS). However, there are a number of concerns with these techniques (Brazier et al, 1999). The direct and choice-less nature of the VAS task has been criticised (Bleichrodt and Johannesson 1997) and VAS data may be subject to end point and context bias (Torrance et al, 2001). Although SG and TTO are often identified as preferred over VAS due to their choice based theoretical underpinnings (Brazier et al, 2006), the values produced by these methods are influenced by factors beyond the respondents preference for the health state including time preference, risk attitude and loss aversion (Bleichrodt, 2002) . For these reasons, there is increasing interest in using ordinal methods to estimate cardinal values for health states to calculate quality adjusted life years

Until very recently, the use of ordinal data in health state valuation such as from ranking or discrete choice experiments (DCE) has largely been ignored. Ranking exercises have traditionally been included in health state valuation studies as a warm up procedure to familiarise the respondent with the set of health states to be valued and with the relative value of health states. Often these data may not be used at all in data analysis, or they may be used to check consistency between the ordinal ranking of health states and the ranking of health states according to their actual values obtained using a standard elicitation technique e.g. TTO or SG (Furlong et al, 1990). Kind (1996) identified Thurstone's law of comparative judgement as a potential theoretical basis for deriving cardinal values from rank preference data (Kind, 1996). Thurstone's method considers the proportion of times that one health state (A) is considered worse than another health state (B). The preferences over the health states are represented by a latent cardinal utility function and the likelihood of health state A being ranked above health state B when health state B is actually preferred to health state A is a function of how close to each other the states lie on this latent utility function.

Salomon (2003) used conditional logistic regression to model rank data from the UK MVH valuation of the EQ-5D. He was able to estimate a model that was comparable to the original TTO model by rescaling the worst state using the observed TTO value. Other methods of rescaling were also considered, including normalization to produce a utility of 0 for death, but these were found not to provide the best fitting predictions. McCabe et al (2006), using similar methods, presented evidence to suggest that rank data that produced cardinal health state valuation models for two generic measures of health status, the HUI2 and SF-6D, were very similar to the original SG models.

DCEs have their theoretical basis in random utility theory (McFadden, 1973; Hanemann, 1984; Ryan 1996). Although DCEs have become a very popular tool for eliciting preferences in health care, the vast majority of published studies using DCE methodology have tended to focus upon the possibility that individuals derive benefit from non-health outcomes and process attributes in addition to health outcomes. A limited number of studies have used DCEs to estimate values for different health state profiles (Hakim and Pathak, 1999; Johnson et al., 2000; McKenzie et al., 2001, Ryan et al, 2006) although none to date have linked these values to the full-health dead scale required for the calculation of QALYs.

This study sought to examine the potential of ranking and DCE data to estimate a preference-based index for a condition specific measure related to sexual quality of life, and to compare the results to models estimated using TTO data and observed TTO health state values.

## 2. Methods

### 2.1. Sexual quality of life questionnaire

The sexual quality of life questionnaire (SQOL) was originally developed as a measure of sexual quality of life for use in a clinical trial setting (Symonds et al 2005). The SQOL has 3 dimensions and 18 items with 6 responses each from completely agree to completely disagree. Each dimension is scored by summing the responses to each item (where each response is coded from one: completely agree to six: completely disagree). In its current form SQOL has a very limited role in assessing cost effectiveness. To extend the scope of the SQOL for use in economic evaluation, values were required to be elicited for health states derived from the SQOL in order to make it preference based .

The current SQOL would generate many millions of health states that would be too large for valuation. The first task of this study was to derive a health state classification amenable to valuation. A preliminary study was undertaken in order to construct a simplified health state classification from the SQOL using a sample of items selected using psychometric criteria

(Brazier and Ratcliffe, 2004). The resultant health state classification system, the SQOL-3D comprised three dimensions: sexual performance, sexual relationship and sexual anxiety; with four levels attached to each dimension (Table 1). A health state is formed by selecting one level from each dimension and in this way 64 health states can be defined (i.e. 4*4*4) by the SQOL-3D .

Table 1 here

Each respondent was asked to value eight health states plus the PITS state - the health state comprising the lowest level on each of the three dimensions (see Table 2 for a sample of health states defined by the SQOL). These 64 states were grouped into 8 samples or blocks of 8 states to reflect a range of health states defined by the classification rather than predominantly a 'good' or 'bad' selection of health states.

Table 2 here

*2.2: Valuation survey*

Interview

The aim was to interview a representative sample of 200 adult members of the general population. Consenting adults were visited in their home by an interviewer to conduct the valuation study. A small pilot study (n=18) was undertaken in advance of the main study to check that interviewees understood the task and were answering the questions as expected.

Prior to the elicitation of health state values using the TTO method, respondents were asked to rank a set of health states from best to worst. The ranking set contained 11 health states in total, the 9 health states which were subsequently valued using the TTO (including the PITS state), plus the best SQOL health state containing the most desirable levels on all dimensions and immediate death. The second stage of the interview involved obtaining TTO valuations of the health states defined by the classification. The main valuation survey was undertaken using the Measurement and Valuation of Health (MVH) group version of TTO with a visual prop (MVH Group, 1995).

The TTO elicitation task asks people to imagine they will be in a state (j) for 10 years, and then asks them to consider a number of shorter periods in perfect health (p). At the point where respondents are unable to choose between state j and time period p in perfect health, the value of state j is given as p/10. It is important to note that the upper anchor was therefore perfect health and not the best state defined by the SQOL classification. This is different from the valuation of generic preference based measures such as the EQ-5D which used the best state defined by the EQ-5D classification. This is because the best state defined by a condition specific measure like the SQOL is not likely to be perfect health. For calculating QALYs it is necessary to ensure that the results lie on the scale where 1 is perfect health and 0 is equivalent to being dead. Respondents were initially taken through a practical TTO to help them understand the task. They were then asked to undertake a total of 9 TTO tasks. The interview then had a series of socio-demographic questions. Finally, they were asked whether they would be willing to participate in a further postal survey.

Follow-up postal survey

In order not to over burden respondents at the interview, it was decided to administer the DCE by post four weeks after the interview.

A computer programme developed by Huber and Zwerina (2000) used in the statistical package SAS was applied to obtain an optimal statistical design for the DCE based upon (i) level balance (ii) orthogonality (iii) minimum overlap and (iv) utility balance. Such a design reduces the possible combinations of attributes and their respective levels (or scenarios) to a manageable number for the purposes of a mail out survey questionnaire whilst retaining maximum statistical efficiency for the estimation of model parameters.

The programme produced 12 pairwise choices for comparison. The 12 pairwise choices were randomly distributed between two versions of the questionnaire comprising 6 pairwise choices in each. For each health state pair, respondents were asked to indicate which health state they considered as better (see Appendix 1 for an example of a discrete choice question included within one of the choice sets).

The two versions of the DCE questionnaire were randomly administered by post to all consenting adults approximately four weeks after the completion of the TTO interview. A reminder was sent out to all non-respondents approximately four weeks after the initial questionnaire.

2.3. Data analysis - TTO

The data from the TTO valuation exercise were analysed using two main approaches based upon aggregate and individual level modelling respectively (Brazier et al, 2002). Firstly, ordinary least squares (OLS) was used to estimate a mean level model: Model 1. The mean health state values were the dependent variable and the independent variables were a series of dummy explanatory variables representing each level of the three dimensions of the SQOL. The mean level model is defined as:

$$Y_i = f(\beta' \boldsymbol{x}_{ij}) + \epsilon_i \qquad (1)$$

Where the dependant variable $Y_i$ is the value (mean TTO value) for each health state (i) and $\boldsymbol{x}$ is a vector of dummy explanatory variables ($x_{\partial\lambda}$) for each level $\lambda$ of dimension $\partial$ of the simplified SQOL classification. For example, $x_{31}$ denotes dimension $\partial$ = 3 (sexual anxiety), level $\lambda$ = 1 (thinking about your sex life you never feel anxious). For any given health state $x_{\partial\lambda}$ will be defined as:

$x_{\partial\lambda}$ =1, if for this state dimension $\partial$ is at level $\lambda$

$x_{\partial\lambda}$ =0, if for this state, dimension $\partial$ is not at level $\lambda$

There are 9 of these terms in total with level $\lambda$ = 1 acting as a baseline for each dimension. Hence for a simple linear model, the intercept (or constant) represents state 111, and summing the coefficients of the 'on' dummies derives the value for all other states. $\epsilon_i$ is the error term which is assumed to be independent with constant variance structure.

Secondly, a one way error components random effects model: Model 2 was specified which takes account of the repeated measurement aspect of the data whereby multiple responses are obtained from the same individual (Diggle et al, 2002).

The random effects model is defined as (Brazier et al, 2002):

$$Y_{ij} = f(\beta'\boldsymbol{x}_{ij}) + \epsilon_{ij} \qquad (2)$$

Where i=1,2 …n represent individual health state values and j = 1,2…m represents respondents. The dependant variable $Y_{ij}$ is the disvalue (1-mean TTO value) for health state i valued by respondent j, $\boldsymbol{x}$ is a vector of dummy explanatory variables ($x_{\partial\lambda}$) defined as previously and $\epsilon_{ij}$ is the error term which is subdivided as follows:

$$\epsilon_{ij} = u_j + e_{ij} \qquad (3)$$

Where $u_j$ is respondent specific variation and $e_{ij}$ is an error term for the $i$th health state valuation of the $j$th individual, and this is assumed to be random across observations. A one way error components fixed effects model can also be specified. This differs from the random effects specification in that the respondent specific effects are not assumed to be random but are a set of fixed effects to be estimated, together with the vector of coefficients on the explanatory variables. The selection of the most appropriate model specification was informed by the Hausman test (Hausman, 1978).

2.4 Data analysis: DCE

The data from the DCE survey were analysed using a random effects probit model: Model 3. Again it uses an additive specification as specified in equation (2). The estimated coefficients and their statistical significance (or otherwise) indicate the relevant importance of the different levels of the dimensions on individual preferences.

2.5 Data analysis: Ranking

The rank ordered logit model was used to analyse the ranking data: Model 4. This model is based upon the assumption that the respondent makes a series of selections from smaller and smaller groups. Thus in ranking 11 health states (as was the case for this study with 9 states being valued plus full health and immediate death) we assume that the respondent chooses the most preferred state from the full set, then chooses the most preferred state from the remaining 10 etc until all health states have been assigned a rank between 1 and 11. The independence of irrelevant alternatives assumption is required to characterise this process as equivalent to a series of pairwise choices i.e. the ranking of the pair is not affected by the other states that are ranked in the same exercise (Luce, 1959).

The rank ordered logit model states that respondent $j$ has a latent utility function for state $i$, $U_{ji}$ and given the choice of two states $i$ and $k$, the respondent will choose state $i$ over state $k$ if $U_{ji} > U_{jk}$.

The expected value of each unobserved utility was assumed to be a linear function of the categorical levels on the dimensions of the SQOL. Following the approach taken by Salomon (2003) and McCabe et al (2006), the general model specification for each individual's cardinal utility function for state $j$ is $U_{ij}$

$= \mu + \epsilon_{ij}$ where $\mu_j$ is representative of the tastes of the population and $\epsilon_{ij}$ represents the particular tastes of the individual. If the error term $\epsilon$ has an extreme value distribution, then the odds of choosing state *j over* state *k* are $exp\{\mu_j - \mu_k\}$.

2.6 Scaling

The DCE and rank model values (Models 3 and 4) produce predicted valuations on an interval scale such that meaningful comparisons of differences are possible but the origins and units of the scale are defined arbitrarily by the identifying assumptions in the model (Salomon, 2003). In order to infer cardinal valuations from the DCE and rank models on a scale where zero is dead and one is perfect health it is necessary to re-scale the estimated valuations for health states. Two alternatives were considered. Firstly, re-scaling both the rank and DCE predicted values such that the lowest value (relating to the PITS state) was anchored at the lowest value for the PITS state predicted by the mean level TTO model (0.672) and the highest value (relating to the best SQOL heath state) was anchored at the highest value for the best SQOL state predicted by the mean level TTO model (0.946). Secondly, re-scaling the rank model coefficients by dividing each level coefficient by the coefficient relating to death: Model 5. This re-scaling option normalises the rank data to produce a utility value of 0 for death (Salomon, 2003). Unfortunately, this method could not be used to re-scale the DCE data also since none of the pairwise health state comparisons included in the DCE questionnaire contained the state dead.

## 2.4 Results

Out of the 376 useable addresses contacted for interview, 207 individuals agreed to participate (a 55% response rate). For the DCE postal follow up survey a response rate of 49% was achieved (102/207) after one reminder. The characteristics of the respondents to the interview and the follow up postal survey respectively are presented in Table 3. The characteristics of respondents to both the interview and the survey were broadly similar with the majority of respondents being female, married and in full-time employment.

Descriptive statistics for the 64 health states are presented in Table 4. Mean TTO health state values range from 0.643 to 0.966 and standard deviations between 0.10 and 0.36. Most health states had 20-30 observations with the PITS state having 207 (i.e. all respondents).

Table 3 here

Table 4 shows the results for the mean and random effects models for the TTO, the DCE and ranking models. The dimension level dummies represent progressively worse problems on each dimension compared to the baseline. As such the coefficient estimates are expected to be negative and increasing in absolute size. An inconsistent result occurs where a coefficient on the main effects dummies decreases in absolute size with a worse level.

Table 4 here

For the mean level TTO (Model 1) all of the coefficients have the expected negative sign, with the exception of the movement from level 1 to level 2 in sexual relationship which is positive (though very small and not signficant). Five of the 9 dimension level coefficients are statistically significant ($p<0.05$), along with the constant term. With the exception of level 2 to 3 of the dimension relating to sexual performance, the coefficient estimates increase with absolute size as the level of each dimension worsens. The explanatory power of the mean level model is 0.517.

The Hausman test suggests that random, rather than fixed effects is the most appropriate model specification ($Chi^2$ = 7.50 p $Chi^2$ = 0.221). For the random effects TTO (Model 2) the results are quite similar in that all of the coefficients have the expected negative sign and increase with size as the level worsens. In total, 8 of the 10 coefficients are statistically significant ($p<0.05$).

The ability of the mean level TTO model to predict observed TTO values is superior to the random effects model, resulting in fewer errors greater than 0.05 and 0.10 in absolute value. Furthermore, the mean model has a mean absolute error (MAE) of 0.040 compared to 0.072. In both models the predictions are unbiased (*t*-test) indicating that neither model systematically over or under estimates the observed mean TTO. However, the Ljung-Box (LB) statistics reveal auto correlation in the prediction errors of both models, when the errors are ordered by actual mean health state valuation.

For the DCE model (Model 3), all of the coefficients have the expected negative sign, and 5 of the 10 coefficients are statistically significant ($p<0.05$).

The coefficient estimates increase with absolute size as the level of each dimension worsens with the exception of the movement from level 2 to level 3 in sexual anxiety (although this inconsistency is small and does not relate to statistically significant dimension levels). For the rank ordered logit models: Models 4 and 5 the results have the expected negative sign and increase with size as the level worsens with the exception of the movement from level 1 to level 2 in sexual anxiety. In total, 9 of the 10 coefficients are statistically significant ($p<0.05$).

The ability of the DCE and ranking models to predict observed mean TTO is broadly similar both in terms of their MAEs compared to observed mean TTO and in the number of differences compared to observed TTO greater than 0.05 and 0.10 in absolute value. In contrast to the TTO models, the DCE and both ranking models produce biased predictions (*t*-test). The LB test found evidence of a systematic pattern in the differences of the predictions from the ranking model though not the DCE model. As would be expected, neither the ranking or DCE models perform as well as the mean level TTO model in terms of their ability to replicate TTO observed values.

Figure 1 illustrates how re-scaling the raw rank predicted values (Model 4) according to the predicted TTO values for the best and worst SQOL health state effectively assumes a linear relationship and fits the predicted mean level TTO values well. However, probably because even the worst SQOL health is relatively mild in terms of severity, this method of re-scaling does not predict a utility value of 0 for death and so the relationship is not linear. When the rank model coefficients are rescaled by using a quadratic functional form to produce a value of 0 for death (Model 5) the predicted values for the rank data do not correspond as well to the mean level TTO values.

Figure 1 here

The predictions of Models 1-5 are compared graphically in Figures 2-6. The health states have been ordered simply in terms of their state number, with 444 at the start as the most severe state (i.e. level 4 on all dimensions) to the best state 111. This does not represent a monotonic scale, but broadly speaking the value of states increases when moving from left to right along the horizontal axis. It can be seen from Figure 2 that values predicted by the mean level TTO model (model 1) follow fairly closely the observed TTO values, with no discernible pattern. Figure 3, suggests very little differences between the RE TTO (model 2) and the mean level TTO values where as the mean level TTO values lie above the DCE values re-scaled according to the values for the pits and best SQOL health states (Model 3) for the vast majority of states (Figure 4). By contrast, the rank values re-scaled in an identical manner (Model 4) shown in Figure 5 lie below the predicted TTO values for more severe states and converge towards the predicted mean TTO values at very mild states with the exception of the PITS state and the best SQOL health states which are set to be equal. When the rank values are re-scaled using death as the bottom anchor (Model 5), the results, presented in Figure 6, indicate that the re-scaled rank values lie markedly below the predicted TTO values for more severe states and above the predicted TTO values for very mild states.

Figures 2-6 here

Finally, we have examined the ability of the models to predict the logical ordering of pairs of SQOL states, where one state should be preferred to another because it is better on at least one dimension, but no worse on any other dimension. In this respect we found that both the mean level TTO (model 1) and the random effects TTO (model 2) performed best with no logical inconsistencies whereas the ordinal models fare worst with the DCE (model 3) exhibiting 7 logical inconsistencies and rank models (models 4 and 5) having 17 and 15 logical inconsistencies respectively.

## 3. Discussion

The paper has presented the results of estimating a preference-based index for a condition specific health state classification using rank and DCE data and comparing the results to a conventional TTO model. Previous research has used rank data, but to our knowledge this is the first study to use DCE data to estimate health states values on the full health-dead scale required to calculate QALYs.

As would be expected the TTO models faired better than the ordinal models in replicating observed TTO valued. The RE TTO model (2) performed only slightly better than the rank (4 and 5) and DCE models (3) in terms of MAE. However, the latter two models suffered from the presence of bias and systematic differences between their predictions and the predicted and observed TTO values. These findings contrast somewhat with the results from modelling rank data for the HUI2 and SF-6D where the rank data were broadly comparable to actual SG (McCabe et al, 2006), though the analysis of rank data for the EQ-5D found differences for the rescaling against being dead (check Salomon, 2004). As commented on in McCabe et al (2006), there is no reason why models estimated from ordinal data should generate the same values as those produced by conventional cardinal methods. More research is needed to compare ordinal and cardinal methods, but these results support the view that they do generate different values.

This paper has also compared the ability of TTO to predict the logical orderings of health states compared to the ordinal methods. It might be expected that models estimated from ordinal data would perform better in this regard. However, the random effects TTO model performed best. This may be due to the biases found in both the DCE and ranking models

This study has highlighted a number of methodological issues which warrant further investigation. In relation to the ranking data analysis, the independence of irrelevant alternatives assumption which characterises the selection process as equivalent to a series of pairwise choices and assumes that the ranking of the pair is not affected by the other states that are ranked in the same exercise is a strong assumption which may be criticised as unrealistic (McCabe et al, 2006). In this respect, other variants of ordinal and discrete choice data collection strategies which do not rely upon this assumption, e.g. best worst scaling (Marley and Louviere, 2005) warrant further investigation in a health care context. In addition, further empirical research is required to assess the sensitivity of health state values produced by ordinal valuation techniques to framing effects that may produce significant differences in responses including subtle variants in question wording, context and modes of administration.

We found that the two ordinal methods produced different results. DCE data produced substantially higher values than the ranking data. However, it can be argued that the DCE values were not based upon a 'pure' test of this method since the values were anchored externally using the predicted TTO value for the PITS and best SQOL health states. The DCE was administered by post following the TTO interviews and so the respondents were 'warmed up' in that they were already familiar with the health states to be compared. Furthermore, only a sub- sample responded to the postal survey although they were broadly similar in characteristics to respondents from the main interview study.

Ordinal measurement strategies such as ranking or DCE may have considerable practical advantages over TTO and SG because it can be argued that they place a lower cognitive burden on respondents and do not require such a high degree of abstract reasoning. However, this assertion needs to be subject to further research. In addition ordinal measurement strategies are not contaminated by issues relating to time preference or attitudes to risk, factors affecting TTO and SG generated health states values respectively. Further empirical studies are required to more fully determine the potential for ordinal health state valuation data to reflect cardinal preferences.

Whilst re-scaling the raw rank and DCE predicted values in reference to the lowest and highest predicted TTO values (Models 3 and 4) provided better fitting estimates in this study than re-scaling the rank model coefficients in reference to the value for death (Model 5), fixing the scale in reference to a value of zero for death may be considered more appropriate in facilitating normalisation on a scale that will enable the estimation of QALY's because it does not need to rely upon information derived from another valuation method (i.e. TTO). In this respect, the inclusion of the state dead within the DCE pairwise health state comparisons would also enable this method of re-scaling to be employed for DCE data. However, it should also be noted that for condition specific instruments where the worst health state appears relatively mild on the full health death scale, this approach can be problematic, as was found with the SQOL. Further empirical work is required to investigate the optimal method of re-scaling raw rank and DCE predicted values for generic and condition specific instruments and the extent to which this may vary according to the method of elicitation and the instrument under consideration.

**References**


Brazier JE, Deverill M, Harper R, Booth A (1999). A review of the use of health status measures in economic evaluation. *Health Technology and Assessment* 3 (9).

Brazier J, Ratcliffe J (2004). Survey comparing original response choices to items of the SqoL to the levels of the SQoL state classification – Preliminary findings. Report for Pfizer limited.

Brazier J, Ratcliffe J, Salomon J, Tsuchiya A (2006). The measurement and valuation of health benefits for economic evaluation. Oxford University Press, Oxford.

Brazier J, Roberts J, Deverill M. The estimation of a preference based single index measure for health from the SF-36 (2002). *Journal of Health Economics* 21: 271-292.

Brazier J, Tsuchiya A, Busschbach J, Stolk E (2002). Issues in estimating a preference based index for condition specific measures. Presentation at the International Health Economics Association meeting, San Francisco, USA.

Brooks R, Rabin R, De Charro F (2004). *The measurement and valuation of health status using EQ-5D: a European perspective*. Kluwer Academic publishers, London.

Diggle PJ, Heagerty P, Liang KY, Zeger SL (2002). Analysis of longitudinal data (2nd edition). Oxford University Press, Oxford.

Dowie J (2002). Decision validity should determine whether a generic or condition specific HRQOL measure is used in health care decisions. *Health Economics* 11: 1-8.

Feeny DH, Furling WJ, Torrance GW *et al* (2002). Multiattribute and single attribute utility function – the health utility index mark 3 system. *Medical Care* 40: 113-128.

McCabe C, Brazier J, Gilks P, Tsuchiya A, Roberts J, O'Hagan A, Stevens K (2006). Using rank data to estimate health state utility models. *Journal of Health Economics* 25(3): 418-431.

MVH Group (1995). *The measurement and valuation of health: Final report on the modelling of valuation tariffs*. Centre for Health Economics, University of York.

Propper C (1995).The disutility of time spent on the United Kingdom's National Health Service waiting lists. *The Journal of Human Resources*, 30: 677-700.

Revicki DA, Leidy NK, Brennan-Diemer F et al (1998). Integrating patients preferences into health outcomes assessment: the multiattribute asthma symptom utility index. *Chest* 114: 998-1007.

Ryan M, Farrar S (1994). A pilot study of using conjoint analysis to establish the views of users in provision of orthodontic services in Grampian*. Health Economics Research Unit Discussion Paper 07/94*. University of Aberdeen, Aberdeen.

Ryan M (1996). The application of conjoint analysis in health care. Office of Health Economics publications, London.

Salomon JA (2003) Reconsidering the use of rankings in the valuation of health states: a model for estimating cardinal values from ordinal data.

Salomon JA, Murray CJ (2004). A multi-method approach to measuring health state valuations. *Health Economics* 13(3): 281-290.

Stolk EA, Busschbach JJV (2003). Validity and feasibility of the use of condition specific outcome measures in economic evaluation. *Quality of Life* Research 12: 363-371.

**Appendix 1: Example of choice question included in DCE questionnaire**

**Pair 1**

| **Health State A** | **Health State B** |
|---|---|
| Your sexual performance is good | Your sexual performance is adequate |
| Your sexual relationship is never poor | Your sexual relationship is rarely poor |
| Thinking about your sex life you some times feel anxious | Thinking about you sex life you rarely feel anxious |

**Which health state do you think is better?** ***(please tick one box only)***

| **A** | **B** |
|---|---|
| | |

**Table 1: Dimensions and levels chosen for the simplified SQOL classification**

1. Sexual performance
   - Your sexual performance is good
   - Your sexual performance is adequate
   - Your sexual performance is sometimes inadequate
   - Your sexual performance is inadequate

2. Sexual relationship
   - Your sexual relationship is never poor
   - Your sexual relationship is rarely poor
   - Your sexual relationship is sometimes poor
   - Your sexual relationship is always poor

3. Sexual anxiety
   - Thinking about your sex life you never feel anxious
   - Thinking about your sex life you rarely feel anxious
   - Thinking about your sex life you sometimes feel anxious
   - Thinking about your sex life you always feel anxious

| Table 2: a sample of health states defined by the SQOL |
| --- |
| **s124**<br><br>Your sexual performance is good<br><br>Your sexual relationship is rarely poor<br><br>Thinking about your sex life you always feel anxious |
| **s212**<br><br>Your sexual performance is adequate<br><br>Your sexual relationship is never poor<br><br>Thinking about your sex life you rarely feel anxious |
| **PITS: s444**<br><br>Your sexual performance is inadequate<br><br>Your sexual relationship is always poor<br><br>Thinking about your sex life you always feel anxious |

**Table 3 : Characteristics of respondents to interview and follow up postal survey**

| | Interview (n=207) | Follow up postal survey (n=102) |
|---|---|---|
| % | | |
| Age in years: | | |
| 18-25 | 7 | 6 |
| 26-35 | 31 | 30 |
| 36-45 | 25 | 24 |
| 46-55 | 20 | 20 |
| 56-65 | 17 | 20 |
| Female | 66 | 75 |
| Married | 57 | 61 |
| Renting property | 20 | 20 |
| In FT employment | 61 | 66 |
| Highest qualification: | | |
| Degree | 22 | 27 |
| Education after min. school leaving age | 51 | 59 |
| Found valuation task difficult[a] | 24 | 12 |
| Poor understanding of valuation task[b] | 6 | N/A |

[a] Judged by respondent

[b] Judged by interviewer

**Table 3: Descriptive statistics for the TTO valuations of the SQOL-3D**

| State | N | Min. | Max. | Mean | SD |
|---|---|---|---|---|---|
| pits: s444 | 207 | 0.025 | 1 | 0.696 | 0.299 |
| s443* | 42 | -0.88 | 1 | 0.694 | 0.363 |
| s442 | 26 | 0.025 | 1 | 0.688 | 0.323 |
| s441 | 26 | 0.1 | 1 | 0.659 | 0.289 |
| s434 | 24 | 0.025 | 1 | 0.694 | 0.124 |
| s433 | 22 | 0.125 | 1 | 0.781 | 0.238 |
| s432 | 20 | 0.325 | 1 | 0.791 | 0.24 |
| s431 | 24 | 0.325 | 1 | 0.869 | 0.18 |
| s424 | 23 | 0.175 | 1 | 0.836 | 0.241 |
| s423 | 23 | 0.025 | 1 | 0.824 | 0.257 |
| s422 | 25 | 0.225 | 1 | 0.805 | 0.271 |
| s421 | 26 | 0.3 | 1 | 0.791 | 0.218 |
| s414 | 24 | 0.025 | 1 | 0.697 | 0.285 |
| s413 | 22 | 0.275 | 1 | 0.84 | 0.205 |
| s412 | 21 | 0.375 | 1 | 0.843 | 0.214 |
| s411 | 24 | 0.275 | 1 | 0.851 | 0.194 |
| s344 | 22 | 0.325 | 1 | 0.767 | 0.259 |
| s343* | 40 | 0.025 | 1 | 0.72 | 0.322 |
| s342 | 25 | 0.375 | 1 | 0.811 | 0.214 |
| s341 | 27 | 0.1 | 1 | 0.692 | 0.266 |
| s334* | 43 | 0.075 | 1 | 0.796 | 0.27 |
| s333 | 23 | 0.025 | 1 | 0.852 | 0.249 |
| s332 | 23 | 0.375 | 1 | 0.818 | 0.242 |
| s331 | 26 | 0.475 | 1 | 0.798 | 0.203 |
| s324 | 25 | 0.025 | 1 | 0.8 | 0.277 |
| s323 | 22 | 0.025 | 1 | 0.825 | 0.285 |
| s322 | 24 | 0.3 | 1 | 0.836 | 0.245 |
| s321* | 43 | 0.325 | 1 | 0.895 | 0.163 |
| s314 | 24 | 0.025 | 1 | 0.824 | 0.274 |
| s313 | 24 | 0.075 | 1 | 0.865 | 0.23 |
| s312 | 23 | 0.025 | 1 | 0.895 | 0.211 |
| s311 | 23 | 0.025 | 1 | 0.872 | 0.236 |
| s244 | 24 | 0.025 | 1 | 0.643 | 0.309 |
| s243 | 23 | 0.175 | 1 | 0.797 | 0.271 |
| s242 | 20 | 0.375 | 1 | 0.763 | 0.257 |
| s241* | 46 | 0.025 | 1 | 0.795 | 0.262 |
| s234 | 24 | 0.025 | 1 | 0.767 | 0.264 |
| s233 | 21 | 0.325 | 1 | 0.85 | 0.205 |
| s232 | 21 | 0.375 | 1 | 0.882 | 0.183 |
| s231* | 48 | 0.075 | 1 | 0.885 | 0.209 |
| s224 | 24 | 0.175 | 1 | 0.848 | 0.242 |
| s223* | 41 | 0.225 | 1 | 0.88 | 0.163 |
| s222 | 26 | 0.475 | 1 | 0.865 | 0.186 |
| s221 | 24 | 0.525 | 1 | 0.897 | 0.144 |
| s214 | 26 | 0.175 | 1 | 0.713 | 0.279 |
| s213 | 25 | 0.325 | 1 | 0.873 | 0.205 |
| s212 | 23 | 0.025 | 1 | 0.845 | 0.278 |
| s211 | 26 | 0.375 | 1 | 0.913 | 0.17 |
| s144 | 22 | 0.025 | 1 | 0.817 | 0.251 |

**Table 3: Descriptive statistics for the TTO valuations of the SQOL-3D (cont.)**

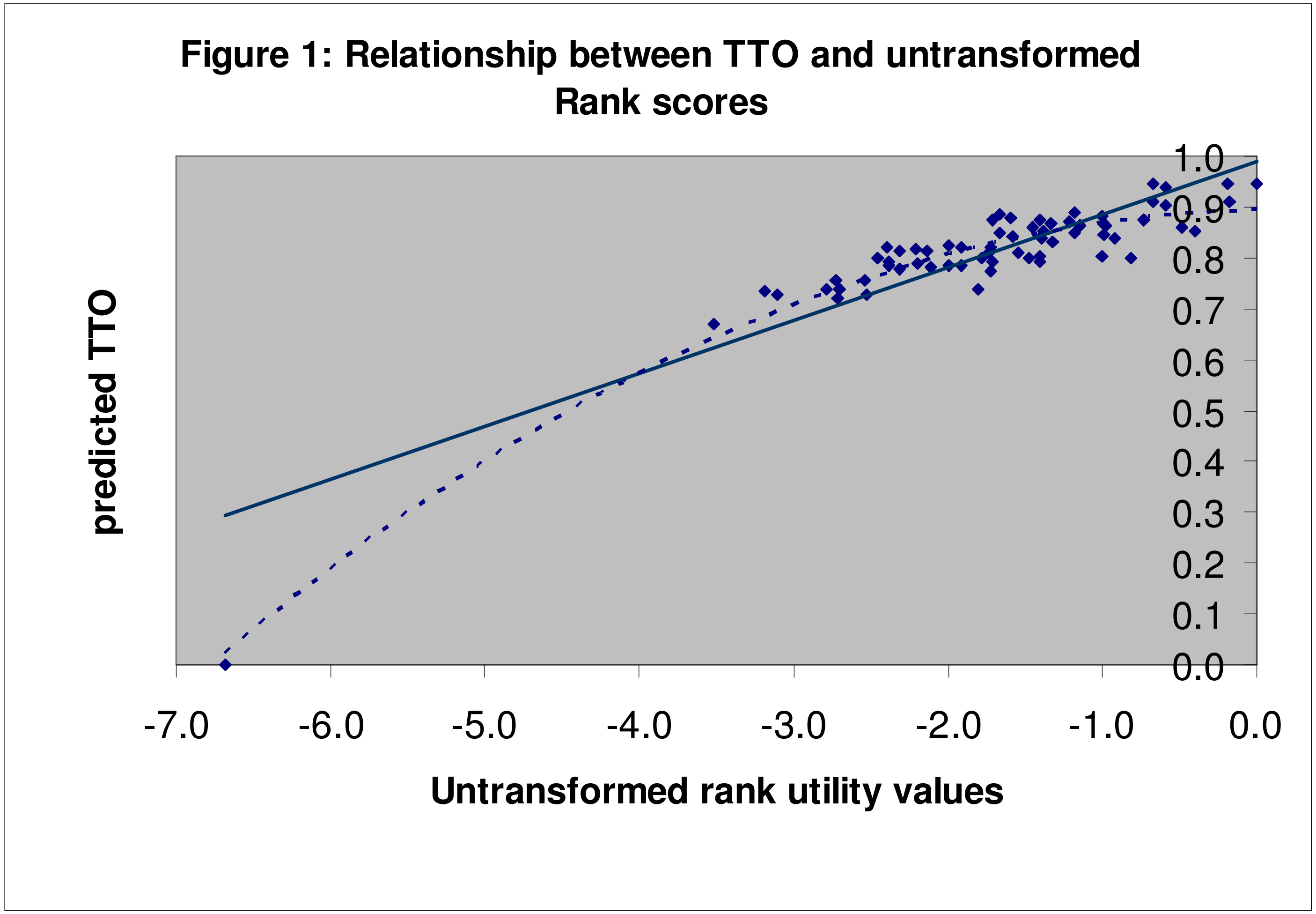
| | | | | | |
|---|---|---|---|---|---|
| S143 | 19 | 0.175 | 1 | 0.797 | 0.271 |
| S142 | 24 | 0.025 | 1 | 0.792 | 0.26 |
| S141 | 25 | 0.025 | 1 | 0.768 | 0.258 |
| S134 | 25 | 0.425 | 1 | 0.83 | 0.201 |
| S133* | 44 | 0.3 | 1 | 0.824 | 0.207 |
| S132 | 25 | 0.275 | 1 | 0.893 | 0.173 |
| S131 | 23 | 0.625 | 1 | 0.917 | 0.121 |
| S124 | 24 | 0.025 | 1 | 0.843 | 0.261 |
| S123 | 22 | 0.675 | 1 | 0.966 | 0.079 |
| S122* | 42 | 0.625 | 1 | 0.962 | 0.087 |
| S121 | 39 | 0.525 | 1 | 0.956 | 0.1 |
| S114 | 21 | 0.375 | 1 | 0.867 | 0.207 |
| S113 | 24 | 0.775 | 1 | 0.938 | 0.084 |
| S112 | 24 | 0.475 | 1 | 0.946 | 0.121 |

- N is somewhat larger for these particular health states as these were valued in pilot survey in addition to main survey

**Table 4: Comparison of mean level TTO, random effects TTO, DCE and Ranking model results**

| | Model 1: Mean level TTO | Model 2: Random effects TTO | Model 3: Random effects DCE | Model 4: Rank ordered logit | Model 5: Rank ordered logit re-scaled utility value of death = 0 |
|---|---|---|---|---|---|
| Lev2 performance | -0.072* | -0.064* | -0.095* | -0.735* | -0.110* |
| Lev3 performance | -0.060* | -0.069* | -0.308 | -0.998* | -0.149* |
| Lev4 performance | -0.126* | -0.127* | -0.712* | -1.726* | -0.258* |
| Lev2 relationship | 0.001 | -0.010 | -0.052 | -0.187 | -0.028 |
| Lev3 relationship | -0.035 | -0.042* | -0.458* | -0.181* | -0.027* |
| Lev4 relationship | -0.084* | -0.111* | -1.183* | -0.975* | -0.146* |
| Lev2 anxiety | -0.002 | -0.001 | -0.076 | -0.482 | -0.072 |
| Lev3 anxiety | -0.009 | -0.028* | -0.071 | -0.406* | -0.061* |
| Lev4 anxiety | -0.065* | -0.060* | -0.904* | -0.812* | -0.121* |
| Constant | 0.946* | 0.961* | 0.070 | N/A | N/A |
| Death dummy | N/A | N/A | N/A | -6.685* | -1.000* |
| *N* | 64 | 207 | 64 | 189 | 189 |
| Inconsistencies[1] | 1 | 0 | 0 | 0 | 0 |
| MAE (compared to actual TTO)_ | 0.037 | 0.072 | 0.077 | 0.069 | 0.083 |
| Adjusted $R^2$ | 0.517 | 0.207 | 0.203 | 0.198 | 0.198 |
| No. > 0.05 | 19 (30%) | 19 (30%) | 18 (28%) | 20 | 22 (34%) |
| No. > 0.10 | 45 (70%) | 38 (60%) | 45 (70) | 42 (66%) | 44 (69%) |
| *t* (mean=0) | -0.301 (p=0.765) | 0.942 (p=0.439) | -13.664 (p=<0.001) | -9.465 (p=<0.001) | -7.227 (p=<0.001) |
| LB | 4.099 (p=0.848) | 86.21 (p=<0.001) | 10.568 (p=0.227) | 36.120 (p=0.076) | 63.973 (p=<0.001) |

* Statistically significant at 5% level




**________Linear relationship between predicted TTO and predicted Rank**

**- - - - - - Quadratic model relationship between predicted TTO and predicted Rank**

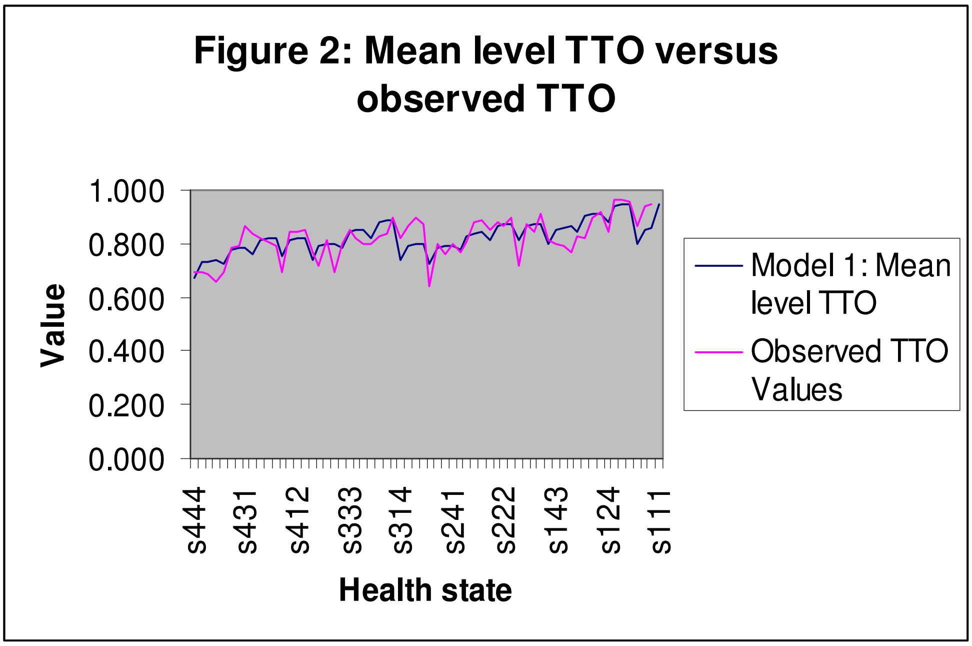


Figure 2: Mean level TTO versus observed TTO
1.000
0.800
0.600
0.400
0.200
0.000
Value
s444
s431
s412
s333
s314
s241
s222
s143
s124
s111
Health state
Model 1: Mean level TTO
Observed TTO Values

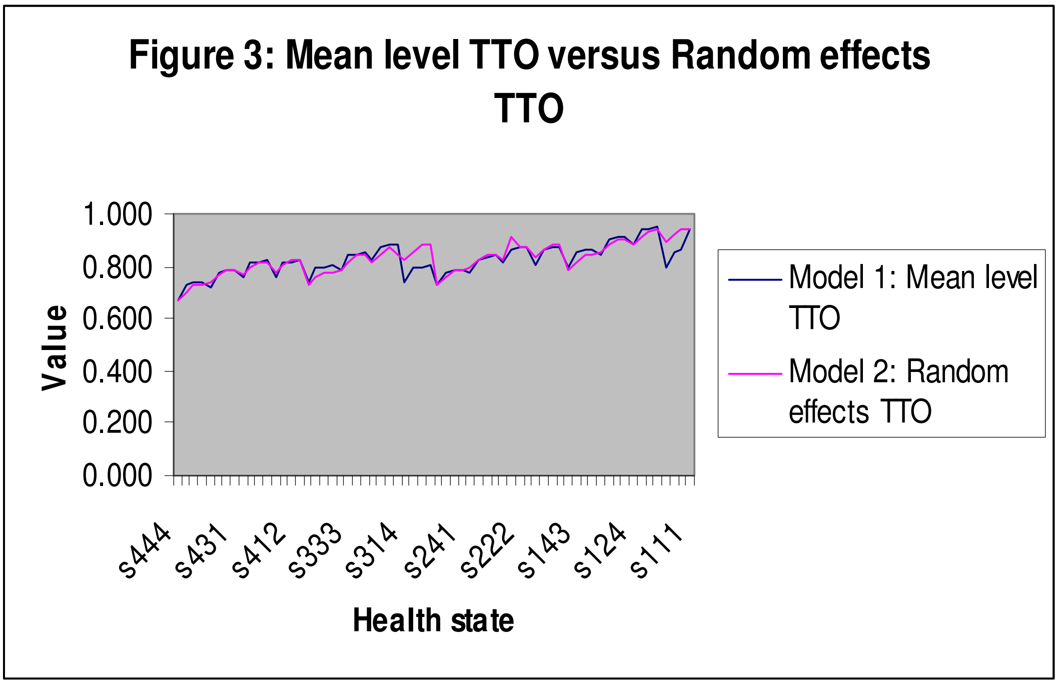
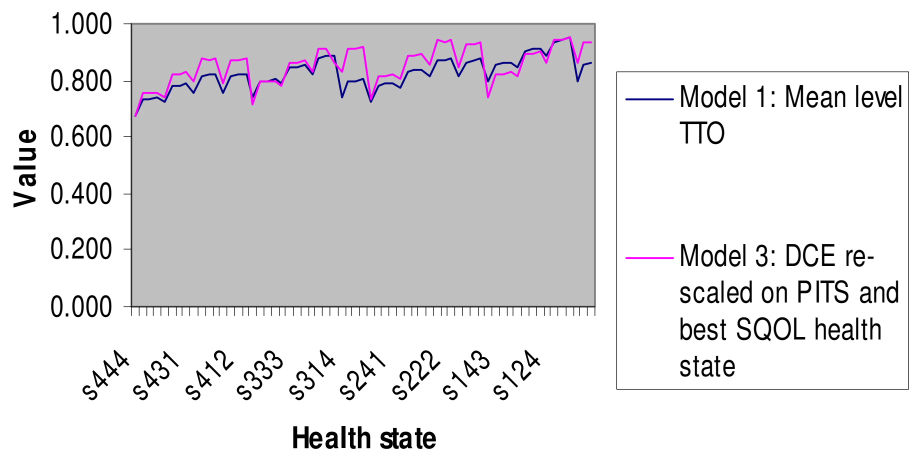


Figure 3: Mean level TTO versus Random effects TTO
1.000
0.800
0.600
0.400
0.200
0.000
Value
s444
s431
s412
s333
s314
s241
s222
s143
s124
s111
Health state
Model 1: Mean level TTO
Model 2: Random effects TTO

# Figure 4: Mean level TTO versus DCE re-scaled




# Figure 5: Mean level TTO versus Rank re-scaled on PITS and best SQOL health state

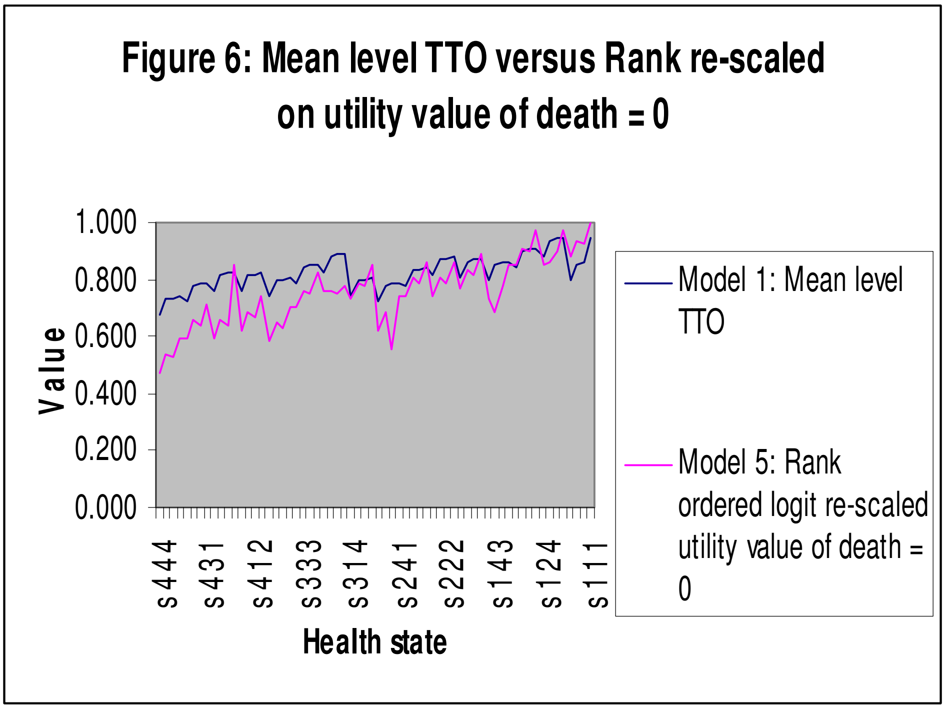


Figure 6: Mean level TTO versus Rank re-scaled on utility value of death = 0
1.000
0.800
0.600
0.400
0.200
0.000
Value
s444
s431
s412
s333
s314
s241
s222
s143
s124
s111
Health state
Model 1: Mean level TTO
Model 5: Rank ordered logit re-scaled utility value of death = 0