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Abstract

Cardinal preference elicitation techniques such as time trade-off (TTO) and Standard Gamble (SG) receive criticism for their complexity and difficulties in using them in more vulnerable populations. Ordinal techniques such as discrete choice experiment (DCE) and Best Worst Scaling (BWS) are easier, but values generated by them are not anchored onto the full health-dead 1-0 QALY scale required for use in economic evaluation. This paper explores new methods for converting modelled DCE latent values onto the full health-dead QALY scale: (1) anchoring assuming worst state is equal to being dead; (2) anchoring DCE values using dead as valued in the DCE; (3) anchoring DCE values using TTO value for worst state; (4) mapping DCE values onto TTO; (5) combining DCE and TTO data in a hybrid model. We use postal DCE data (n=263) and TTO data (n=307) collected by interview in a general population valuation study of an asthma condition-specific measure (AQL-5D). Methods (4) and (5) using mapping and hybrid models perform best; the anchor-based methods perform relatively poorly. These new methods have a useful role for producing values on the QALY scale from ordinal techniques such as DCE and BWS for use in cost utility analyses.

INTRODUCTION

Economic evaluation measuring outcomes using quality-adjusted life years (QALYs) has increasingly informed resource allocation in recent years. The QALY is a measure of health outcome that combines quality of life with length of life. Quality of life is measured on a full health-dead 1-0 scale, where one equals full health and zero is equal to being dead, with negative values where quality of life is regarded as worse than being dead. For the complex decision problems faced by agencies such as the National Institute for Health and Clinical Excellence (NICE) this has been extremely useful for informing decision making of resource allocation for health care programmes using incremental cost per QALY analyses. The QALY enables comparisons across interventions that impact on mortality, morbidity and both. These comparisons cannot be avoided, and the QALY provides a useful summary measure that enables the full rigours of modern cost effectiveness analysis to be applied. However there remains much debate surrounding the elicitation of utilities to produce the 'Q' quality adjustment weight of the QALY.

Standard cardinal techniques for eliciting preferences for health states have been time trade-off (TTO), standard gamble (SG) TTO, SG and visual analogue scale (VAS). There has been much debate in the literature regarding the best technique. TTO and SG have been regarded by many as superior to VAS for eliciting preferences since they are based on choices that involve sacrificing (i.e. some notion of opportunity costs), although there is often little agreement in values elicited using these two techniques. On the other hand, SG and TTO have been criticised for being too complex for many respondents and effectively disenfranchising important groups in society such as the very elderly and the young, and some cultures. This has led to increasing interest in the use of ordinal techniques, such as pairwise discrete choice experiment (DCE) where respondents choose between two health states and best-worst scaling (BWS) where respondents choose the best and worst attributes of a health state, including application of BWS to measures of capabilities (Coast et al. 2008) and social care outcomes (Netten et al. 2012).

DCE has been used for eliciting utility values for different health care programmes, but has had limited use for eliciting utility values for health states to inform the scoring systems for preference-based measures of health. A small number of studies have used DCE to value health states (Brazier et al. 2011;Burr et al. 2007;Hakim and Pathak 1999;Osman et al. 2001;Ratcliffe et al. 2009;Ryan et al. 2006) but the majority of these have not anchored values on the full health-dead QALY scale. DCE values can be modelled using regression techniques such as conditional logit and probit to produce preference weights for each

severity level of each dimension in the classification system, but these coefficients are expressed on a modelled latent utility value that has arbitrary anchors. Some studies anchor values onto a 1-0 best state-worst state scale (Burr, Kilonzo, Vale, & Ryan 2007;Ryan, Netten, Skatun, & Smith 2006) but this is an arbitrary assumption dependent on the specific dimensions and severity levels included in the classification system. Three published DCE studies have attempted to anchor the modelled latent utility values onto the full-health QALY scale. The first study anchors modelled DCE values using the TTO value for the worst health state defined by the classification system (Ratcliffe, Brazier, Tsuchiya, Symonds, & Brown 2009). This represents a rather crude attempt to anchor DCE values onto a full health-dead scale using just one data point. The second study incorporates a dead state into pair wise DCE tasks and estimates an additive regression model that includes a dummy variable for dead (Brazier, Rowen, Tsuchiya, & Yang 2011). The regression coefficients are normalised onto the full health-dead scale by dividing the coefficient on each level by the coefficient on the dead dummy variable. This method has been criticised (Flynn et al. 2008) as many respondents do not see any states described by the classification system as worse than being dead. While the proportion who do regard any state as worse than dead is as small as 15% in the case of EQ-5D, it is usually higher than this (e.g. 66% for SF-6D) and for these respondents the appropriateness of this method is questioned. The third study incorporated duration into the DCE task. This presents design and modelling challenges that have been addressed (Bansback et al. 2010), since the relationship between quality of life and survival is not additive. However, the incorporation of duration into the DCE task increases the complexity of the task, and does not offer a solution to the increasingly used BWS technique.

This paper explores these methods for anchoring DCE and BWS values onto the full health-dead QALY scale and two new ones. It uses a data set from a general population valuation study of an asthma condition-specific measure (AQL-5D) using TTO and DCE. Alternative methods for anchoring the DCE data onto the full health-dead scale are explored: (1) anchoring assuming worst state is equal to being dead; (2) anchoring the modelled DCE latent variable using dead as valued in the DCE; (3) anchoring the modelled DCE latent variable using the TTO value for the worst state; (4) mapping the modelled DCE latent variable onto TTO; (5) combining DCE and a sample of TTO data in a hybrid model. The comparison of methods will inform researchers about the relative merits of using each method to anchor DCE values onto the full health-dead QALY scale.

METHODS

Health state description

Health states are described using an asthma-specific preference-based measure, AQL-5D, (Young et al. 2011) derived from the Asthma Quality of Life Questionnaire, AQLQ (Juniper EF et al. 1993). AQL-5D has 5 dimensions: concern about asthma, shortness of breath, weather and pollution stimuli, sleep impact and activity limitations each with 5 levels of severity to define a total of 3125 health states (see Table 1).

Valuation surveys

Interview

Interviews were undertaken to elicit health state utility values for a selection of AQL-5D states using TTO from a representative sample of the general population. Respondents were interviewed in their own home by trained and experienced interviewers. At the start of the interview respondents were informed about asthma using an information sheet. To familiarise respondents with the system respondents who had asthma were asked to complete the health state classification system for themselves; respondents who did not have asthma were asked to complete the health state classification system for someone they knew who had asthma or to imagine somebody with asthma. Respondents were then asked to rank 7 intermediate states, full health (health state 11111), worst state defined by the health state classification (health state 55555), and immediate death.

Respondents then valued a practice state using TTO, and this was followed by valuation of the 7 intermediate states and the worst state using TTO, with an upper anchor of full health (health state 11111). The survey used the used the Measurement and Valuation of Health (MVH) study version of TTO, including a visual prop designed by the MVH group (University of York) (Dolan 1997;Gudex 1994). Respondents were then asked questions about their socio-economic characteristics and health service use, how difficult they found the rank and TTO tasks and finally whether they were willing to participate in a postal survey (described below).

The classification system describes too many states for valuation, and a sample of states were selected for valuation using TTO using the specification of a regression model estimated on TTO data to estimate preference weights for all severity levels of each dimension in the classification system, using level 1 as the baseline. Health states were selected using a balanced design, which ensured that every level of every dimension had an equal chance of being combined with each severity level of the other dimensions. The

design selected 98 health states which were then randomly stratified into mixed severity groups of 7 states based on their summed severity score (summing the scores on all 5 dimensions e.g. 22222 has a severity score of 10). These combinations of 7 states made up the card blocks used in the interviews, to ensure each intermediate state was valued an equal number of times and that respondents valued states with a wide range of severity. The worst state is valued by all respondents to increase accuracy for this value and enable responses to be compared across groups of respondents valuing different intermediate states.

Postal survey

Interviewees who had stated in the interview that they were willing to complete a postal survey were mailed a postal DCE questionnaire approximately four weeks after the interviews. The questionnaire was also mailed to a sample of the general public who had not been previously interviewed. At the start of the survey respondents were asked to complete the health state classification system for themselves to help familiarise them with the classification. Respondents were then asked a practice pairwise comparison question followed by a series of 8 pairwise comparisons, where for each comparison respondents were asked to indicate which health state they preferred. Finally respondents were asked questions about their socio-demographic characteristics. Reminders were sent to all non-responders approximately four weeks after the initial questionnaire was sent.

Combinations of health states for the pairwise comparisons were selected using the D-efficiency approach using a specially developed programme (Huber and Zweina 1996) in statistical software SAS. The programme obtained an optimal statistical design based on level balance, orthogonality, minimal overlap and utility balance which reduced the number of pairwise comparisons required for valuation. The programme selected 24 pairwise comparisons which were randomly allocated to four questionnaire versions each with 6 comparisons. Each questionnaire also included two identical pairwise comparisons comparing a severe health state (state 44355) and the worst health state to 'immediate death'.

Modelling health state values

Time trade-off

TTO data was analysed using a one-way error components random effects model via generalised least squares (GLS). This takes account of the structure of the data as each respondent valued multiple health states (Brazier et al. 2002). The model specification was:

$$U_{ij} = f(\mathbf{X}_i\boldsymbol{\beta}) + \varepsilon_{ij} \quad (1)$$

Where U_{ij} represents TTO disvalue (1–TTO value) for health state *i*=1,2 …*n* valued by respondent *j*=1,2…*m*, $\mathbf{X}_i$ represents a vector of dummy variables for each level λ of dimension ∂ of the health state classification system where level λ = 1 is the baseline for each dimension and ε_{ij} is the error term. The error term is subdivided $\varepsilon_{ij} = u_j + e_{ij}$, where u_j is the individual random effect and e_{ij} is the usual random error term for the *i*th health state valuation of the *j*th individual. Other models estimated using this data are reported elsewhere (Yang et al. 2011).

DCE and TTO

DCE data was modelled to produce cardinal utility estimates on a latent utility scale. The DCE data was modelled using a random effects probit model which takes account of the structure of the data where each respondent valued multiple states, using an additive specification as outlined in equation (1) (Ratcliffe, Brazier, Tsuchiya, Symonds, & Brown 2009). This model produced coefficients on a latent utility scale with arbitrary anchors. This model excluded data collected for the pairwise comparisons involving the state 'dead'.

Translating DCE scores onto the full health-dead scale

Method (1): anchoring using worst state equals zero

The coefficients from the Probit model were normalised using $\beta_{r\lambda\partial} = \beta_{\lambda\partial} \Big/ \sum \beta_{5\partial}$ where $\beta_{r\lambda\partial}$ is the rescaled coefficient for level λ of dimension ∂, $\beta_{\lambda\partial}$ is the coefficient for level λ of dimension ∂, and $\beta_{5\partial}$ is the coefficient for the worst level (level 5) of dimension ∂. The coefficients for the worst level of each dimension sum to -1. This method produces utility estimates for all health states anchored on a 1-0 best state-worst state scale.

Method (2): anchoring using the coefficient for 'dead'

Firstly all DCE data including data for the pairwise comparisons involving the state 'dead' was modelled using a random effects probit model (Brazier, Rowen, Tsuchiya, & Yang 2011). The model specification was:

$$U_{ij} = f(\mathbf{X}_{\delta\lambda}\boldsymbol{\beta} + \phi D) + \varepsilon_{ij} \quad (2)$$

Where U_{ij} represents utility for health state *i*=1,2 …*n* valued by respondent *j*=1,2…*m*, $\mathbf{X}_i$ represents a vector of dummy variables for each level *λ* of dimension *∂* of the health state classification system, *D* represents a dummy variable for the state 'dead' and ε_{ij} is the error term. Secondly coefficients for each level of each dimension were normalised by dividing by the dead dummy variable; $\beta_{r\lambda\partial} = \beta_{\lambda\partial} / \Phi$ where $\beta_{r\lambda\partial}$ is the rescaled coefficient for level *λ* of dimension *∂*, $\beta_{\lambda\partial}$ is the coefficient for level *λ* of dimension *∂* and Φ is the coefficient for the dead dummy variable (see (Brazier, Rowen, Tsuchiya, & Yang 2011) for use of this technique in DCE data and (McCabe et al. 2006;Salomon 2003) for use of this technique in rank data).

Method (3): anchoring the worst state using TTO

The coefficients on a latent utility scale estimated in the first stage of method (1) were normalised onto the full health-dead scale using the estimated TTO value of the worst state. This means that the value of the worst state in the DCE model is anchored at the TTO value of the worst state.

Method (4): mapping DCE onto TTO

Mapping is a method often used to estimate utility values for a trial (or study) when a utility measure was not included in the trial. This is achieved by predicting utility values for the trial using the statistical relationship between data included in the trial and the preferred utility measure (see (Brazier et al. 2010) for a recent review of mapping). This mapping principle was used here to estimate TTO values for all states using modelled latent DCE values for all states. By using more than one health state TTO value it should provide a more accurate method.

The probit model estimated on DCE data generates values on a latent utility scale for all 3125 states. Ninety-nine of these states have mean TTO values collected in the interviews. The simple mapping function from TTO to DCE was specified as:

$$TTO_i = f(DCE_i) + \varepsilon_i \quad (3)$$

Where TTO_i represents mean TTO value of health state *i*, DCE represents the modelled latent utility value for health state *i* and ε_i is the error term. The first specification assumes a linear relationship with an intercept, and then squared and cubic terms were added to see whether model performance was improved. Estimation was undertaken using OLS.

The interest in this method is in the use of a small TTO study accompanying a larger DCE survey. One issue is the selection of the potential size of such a TTO survey and so this study examines the valuation of 10, 19 and 99 states. Method (4a) used 10 health states selected by ordering latent DCE utility estimates by severity (using the modelled DCE latent estimate) from mildest to most severe and selecting the states valued 1st, 11th, 22nd, 33rd, 44th, 55th, 66th, 77th, 88th and 99th. Method (4b) used 19 states, the states used in method 4a were supplemented by states valued 6th, 16th, 27th, 38th, 49th, 60th, 71st, 82nd and 93rd. The rationale for choosing 10 and 19 states was logistical; these states can be easily valued by respondents using TTO. The study design for method (4a) requires respondents to value all 10 states using TTO; study design for method (4b) requires respondents to value 10 states, consisting of 9 states plus the worst state using two different card blocs in the interviews. More and different states could have been chosen, but these were selected to provide an indication of how the method performs. Method (4c) used all 99 states in order to examine the degree of improvement from increasing the number of states valued by TTO up to the number required to estimate a well specified TTO algorithm.

Method (5): hybrid models

This method combines TTO data with discrete choice data using both a likelihood approach and a Bayesian approach. The idea behind both approaches has an analogy to survival data where data are combined on patients who died and patients who have not; patients who have died offer exact information, and patients who have not yet died offer censored information. By analogy TTO data give exact information about the utility of a health state and discrete choice data offer censored data that indicates whether the value of one state is higher than the value of another state but not the degree to which it is higher. As with survival analyses, these two sources of data can be brought together using a single likelihood-function. Methods (5a), (5b) and (5c) use individual level TTO data for the states selected in method (4) and all DCE data. Technical details are presented in the Appendix.

Comparison of models

The most important aspect of model performance is accuracy of the estimated utility values anchored onto the full health-dead scale as indicated by the mean observed TTO health state values. . Model performance was assessed using mean absolute difference between observed TTO and predicted health state utility values (MAD) at the health state level, root mean squared difference (RMSD) at the health state level and number of states where MAD

is greater than 0.05 and 0.1 respectively. Predictions from the 5 methods (and their variations) were plotted alongside mean observed values for the 99 states valued by TTO.

RESULTS

The data

The TTO dataset contains 307 successfully conducted interviews, providing a response rate of 40% for suitable respondents answering their door at time of interview. Each intermediate health state was valued 19 to 22 times, and the worst state was valued 307 times. The distribution of TTO values was negatively skewed and mean TTO value for the 99 health states ranged from 0.39 to 0.94. Further details are reported elsewhere (Yang, Brazier, Tsuchiya, & Young 2011).

The DCE dataset contains 263 successfully completed postal surveys. Out of the 307 respondents who were interviewed 168 returned postal DCE questionnaires (55%). Out of the 400 households receiving the postal questionnaire who were not previously interviewed 95 returned questionnaires (24% return rate). Data from all respondents have been pooled since previous analyses showed no significant difference between them (Brazier, Rowen, Tsuchiya, & Yang 2011).

Table 2 reports the socio-demographic composition of the TTO and DCE samples. Both samples are similar, but the TTO sample is younger and healthier, with a higher proportion of males. Self-reported health status using EQ-5D (Dolan 1997) was similar for each sample to the UK EQ-5D norms of 0.85 for females and 0.86 for males (Kind et al. 1999).

TTO model

Table 3 reports the model estimated on TTO data. The majority of coefficients were negative and the size of coefficients were consistent, where more severe levels of each dimension had a larger utility decrement. Three coefficients were positive but small and statistically insignificant.

DCE model

The DCE model producing latent DCE estimates that are unanchored onto a full health-dead 1-0 scale is reported in Table 3. Estimated coefficients for both methods had four inconsistencies, level 2 of concern, breathlessness and pollution and level 3 of pollution, though only level 2 of pollution was statistically significant.

Methods (1) to (3): anchoring

Results for methods (1) and (3) anchor the latent DCE estimates, and have the same inconsistent coefficients as the latent estimates for level 2 of concern, breathlessness and pollution and level 3 of pollution (Table 3). Method (1) anchored coefficients of the DCE model by dividing them by the coefficient for the worst state and method (3) anchored coefficients of the DCE model by dividing them by TTO value for the worst state. Method (2) modelled all DCE data including comparisons involving the 'dead' state and anchored coefficients using the coefficient for 'dead'. This method had three of the four positive coefficients of the latent DCE estimates, and the same coefficient (level 2) was significant. All 3 methods anchored the DCE data similarly and the pattern of the coefficients was similar. The most noticeable differences were at the lower end of the dimensions for concern, short of breath, sleep and activities where methods (2) and (1) in particular produced larger coefficients than method (3) and the TTO model.

Method 4: mapping

Results for method (4) are reported in Table 4. The DCE coefficient is negative and significant across all 3 models. The size of the intercept and the gradient associated with the latent DCE value are similar across models using TTO data collected for 10, 19 and 99 health states (models (4a), (4b) and (4c) respectively). Plots of TTO and DCE data indicated a linear relationship. The inclusion of squared and cubic terms were explored but these variables were insignificant and did not improve model performance.

Method 5: hybrid models

Results for method (5) are reported in Table 5. All models for method (5) have been estimated using both a common likelihood function and a Bayesian method. Overall the coefficients are similar to the TTO model reported in Table 3. Coefficients were larger for sleep and activity level 5 than in the TTO model, as also found for the anchor based models. There was a tendency for the coefficients to move in the direction of the anchor based models with larger coefficients for concern, sleep and activity levels 5, but this was less marked and was not the case for breathing. This tendency was greater for the two models with sub-samples of TTO valued states. For the likelihood model estimates using TTO data for 10 and 19 states alongside all DCE data there are 3 consistencies, though none are significant. The comparable models estimated using the Bayesian method have 4 and 5 inconsistent coefficients though again none are significant.

Comparison of methods

The smallest difference between predicted values and observed mean TTO health state values measured using MAD and RMSD were, as expected, the model estimated on a dataset containing all TTO data, namely the TTO only model (MAD=0.056, RMSD=0.070). This was followed by method (4c) mapping function (MAD=0.054, RMSD=0.069) and method (5c) hybrid model estimated via the likelihood method using all 99 mean TTO health state values (MAD=0.052, RMSD=0.067). Simple mapping functions using 10 and 19 mean TTO health state values almost performed as well (MAD=0.057, RMSD=0.072 and MAD 0.056, RMSD=0.071 respectively). Hybrid models estimated using TTO values for 10 and 19 states also performed well with models estimated using the likelihood method (MAD=0.062, RMSD=0.080 and MAD=0.059, RMSD=0.067) outperforming models estimated using the Bayesian method (MAD=0.067, RMSD=0.084 and MAD=0.066, RMSD=0.083). The mapping (4) and hybrid (5) methods had better model performance than the anchor based methods. Method (3) was the best of the anchor models (MAD=0.075, RMSD=0.093), followed by method (2) (MAD=0.093, RMSD=0.118) then method (1) (MAD=0.129, RMSD=0.161).

These differences in model performance are demonstrated in Figure 1. Method (4) produced the utility estimates that best follow the pattern of observed TTO values. Method (1) consistently under-estimated TTO values, but technically was anchored on a different scale to TTO. Method (2) had more accurate estimates at the upper end of the scale but under-estimation at the lower end of the scale. Method (3) over-estimated the value of most states. Method (5) over-estimated values for the majority of health states, but perhaps to a less severe extent than method (3).

DISCUSSION

This paper explored new methods for converting modelled DCE and BWS latent values for a health state classification system onto the full health-dead 1-0 QALY scale and compared these to methods used in the literature. The first new method mapped modelled DCE latent values onto TTO values. The second method estimated utility decrements for each severity level of the classification system by modelling DCE and TTO data together using a hybrid model. These new methods produce utility estimates that are more similar to TTO estimates than existing methods, and are more appropriate for anchoring DCE values onto the full health-dead QALY scale. The analysis further explored whether these methods would produce accurate utility estimates for studies involving a small-scale TTO survey alongside a

large DCE survey. Both methods produced relatively accurate predictions under these circumstances.

These new methods potentially have a useful role in producing values on the QALY scale using both ordinal DCE and cardinal TTO data that makes best use of the desirable properties of each elicitation technique and elicited data. DCE has the advantage that it is a cognitively simple task and values are not affected by time preference; but faces the challenge of how to convert values onto the full health-dead scale. TTO encapsulates the trade-off between quality and quantity of life; but can be cognitively demanding and data can be expensive to collect. Combining these techniques may also mean that large scale data collection using DCE can be undertaken inexpensively online, and small scale TTO data can be collected by interview as its usability in an online environment is questionable. There has also recently been interest in using DCE and BWS scaling to obtain values from children (Ratcliffe et al. 2011) and elderly users of social care (Netten, Burge, Malley, Potoglou, Towers, Brazier, Flynn, Forder, & Wall 2012).

Anchoring methods (1) to (3) used in the literature did not perform well compared to the new approaches. Method (1) assumed that the worst state equalled zero and required no cardinal data or pairwise comparisons involving the state 'dead', but had no empirical basis. Method (2) involved the use of pairwise comparisons with the state 'dead' and was an adaptation of a method successfully applied in rank data for several generic preference-based measures. Using SF-6D and HUI2 data a regression model with the same specification as equation (2) estimated on rank data was able to predict mean SG health state values reasonably well (McCabe, Brazier, Gilks, Tsuchiya, Roberts, O'Hagan, & Stevens 2006). However when using EQ-5D data the same model substantially over-predicted TTO health state values. Model (2) estimated here replicated these results. The model has also been criticised since it violates the assumptions of random utility theory for the large proportion of respondents who do not value any state as worse than being dead (Flynn, Louviere, Marley, Coast, & Peters 2008). Method (3) anchored the DCE data using a single data point for the TTO value of worst state. This method systematically over-estimated values due to its reliance on a single TTO value.

Method (4) used a simple mapping based approach and achieved good predictions of observed mean TTO health states values. Model performance was not largely affected when the method was estimated using datasets containing TTO values for only 10 and 19 health states respectively. However there will be considerable uncertainty around these mapped

mean health state values. This would need further investigation before these results can be used in economic evaluation, for example using bootstrapping methods to generate confidence limits around these results.

Method (5) used a hybrid model to combine DCE and TTO data and had good model performance. This method is more appealing statistically since it makes better use of the data. Method (5) used individual level data whereas method (4) used mean level data, meaning that method (5) does not suffer from problems associated with having only 10 or 19 data points. For this reason it is somewhat surprising that method (5) did not overwhelmingly outperform model (4). The likelihood model performed better than the Bayesian method across all samples. Further research using these hybrid models is recommended.

One key weakness is the study design of the DCE. The design used a limited number of pair wise comparisons and was based upon the Huber and Zwerina design criteria which, although widely used, do not guarantee optimal designs and on occasion cannot be used to estimate all the main effects of interest (Huber & Zweina 1996). More sophisticated approaches to DCE study design using optimal and near optimal designs are now being recognised and applied in a health care context (Street and Burgess 2007;Viney et al. 2005). It is impossible to completely rule out that the choice of DCE design may have impacted upon the results achieved and further research is required to assess the replicability of the comparative results found here in studies using optimal or near optimal DCE study designs. However, a better DCE design is not likely to alter the results of the comparison of anchoring methods, except that it may improve them all to some degree.

This study looked at DCE in the content of a condition-specific measure. One important question is whether it would hold for BWS and for different classification systems. Research recently completed developing and valuing a generic social care outcome measure (ASCOT) with BWS has also found the mapping method to work well (though it has not been compared to other methods (Netten, Burge, Malley, Potoglou, Towers, Brazier, Flynn, Forder, & Wall 2012).

Ordinal methods such as discrete choice experiment (DCE) are a promising alternative for valuing health state classification systems as they are cognitively easier than commonly used cardinal methods of TTO and SG. However ordinal data has not been widely used to date due to the challenge of anchoring ordinal data onto the 1-0 full health-dead QALY scale. This paper explored two new methods for anchoring ordinal DCE data onto the 1-0 full

health-dead QALY scale using mapping and estimation of a hybrid DCE and TTO model. Both approaches required TTO data, but both performed well with TTO observations for only 10 health states. Anchor-based methods used in the literature performed poorly in comparison to these methods. These new methods potentially have a useful role in producing values on the QALY scale using both ordinal and cardinal data that makes best use of the desirable properties of each elicitation technique and elicited data.

Table 1 Classification system of asthma-specific measure AQL-5D

Concern
1. Feel concerned about having asthma none of the time
2. Feel concerned about having asthma a little or hardly any of the time
3. Feel concerned about having asthma some of the time
4. Feel concerned about having asthma most of the time
5. Feel concerned about having asthma all of the time

Short of breath
1. Feel short of breath as a result of asthma none of the time
2. Feel short of breath as a result of asthma a little or hardly any of the time
3. Feel short of breath as a result of asthma some of the time
4. Feel short of breath as a result of asthma most of the time
5. Feel short of breath as a result of asthma all of the time

Weather and pollution
1. Experience asthma symptoms as a result of air pollution none of the time
2. Experience asthma symptoms as a result of air pollution a little or hardly any of the time
3. Experience asthma symptoms as a result of air pollution some of the time
4. Experience asthma symptoms as a result of air pollution most of the time
5. Experience asthma symptoms as a result of air pollution all of the time

Sleep
1. Asthma interferes with getting a good night's sleep none of the time
2. Asthma interferes with getting a good night's sleep a little or hardly any of the time
3. Asthma interferes with getting a good night's sleep some of the time
4. Asthma interferes with getting a good night's sleep most of the time
5. Asthma interferes with getting a good night's sleep all of the time

Activities
1. Overall, not at all limited with all the activities done
2. Overall, a little limitation with all the activities done
3. Overall, moderate or some limitation with all the activities done
4. Overall, extremely or very limited with all the activities done
5. Overall, totally limited with all the activities done

Table 2 Characteristics of respondents in valuation surveys

	TTO interview sample (n=307)	DCE postal survey (n=263)
Age:		
18-25	11.1%	3.4%
26-35	18.6%	13.3%
36-45	19.9%	17.1%
46-55	16.3%	21.3%
56-65	14.7%	24.3%
>66	19.5%	20.5%
Female	54.7%	56.3%
Self-reported EQ-5D scores:		
Male, female	0.83, 0.84	0.81, 0.82

Table 3 Anchor based methods (1) to (3) – TTO and normalised DCE model estimates

	TTO	Latent DCE estimates	Method (1)	Method (2)	Method (3)
concern2	-0.028	0.053	0.014	0.012	0.008
concern3	-0.044*	-0.104	-0.027	-0.024	-0.015
concern4	-0.054*	-0.394*	-0.102*	-0.099*	-0.058*
concern5	-0.081*	-0.649*	-0.168*	-0.139*	-0.096*
breath2	0.000	0.173	0.045	0.025	0.025
breath3	-0.036*	-0.017	-0.004	-0.008	-0.003
breath4	-0.101*	-0.387*	-0.100*	-0.116*	-0.057*
breath5	-0.116*	-0.632*	-0.164*	-0.138*	-0.093*
pollution2	-0.019	0.375*	0.097*	0.084*	0.055*
pollution3	-0.050*	0.067	0.017	-0.002	0.010
pollution4	-0.058*	-0.153	-0.040	-0.051*	-0.023
pollution5	-0.121*	-0.427*	-0.110*	-0.085*	-0.063*
sleep2	0.018	-0.182	-0.047	-0.022	-0.027
sleep3	0.010	-0.318*	-0.082*	-0.072*	-0.047*
sleep4	-0.033*	-0.636*	-0.165*	-0.125*	-0.094*
sleep5	-0.054*	-0.681*	-0.176*	-0.149*	-0.100*
activity2	-0.039*	-0.218*	-0.056*	-0.056*	-0.032*
activity3	-0.059*	-0.500*	-0.129*	-0.113*	-0.074*
activity4	-0.175*	-1.076*	-0.278*	-0.247*	-0.158*
activity5	-0.197*	-1.476*	-0.382*	-0.335*	-0.217*
Dead dummy				-1.000*	
Number of observations	2456	1559	1559	2077	1559
Number of individuals	307	263	263	263	263
Inconsistencies	2	4	4	3	4
No. predictions >0.05 from observed TTO	19		40	34	24
No. predictions >0.1 from observed TTO	9		33	24	11
MAD	0.056		0.129	0.093	0.075
RMSD	0.070		0.161	0.118	0.093

Notes: *statistically significant at 5% level

Table 4 Method (4) - Mapping DCE onto TTO

	Method (4a) 10 states	Method (4b) 19 states	Method (4c) All states
DCE estimate	-0.142*	-0.141*	-0.118*
Constant	0.916*	0.928*	0.897*
Observations	10	19	99
R-squared	0.97	0.85	0.63
No. predictions >0.05 from observed TTO	50	52	43
No. predictions >0.1 from observed TTO	16	14	13
MAD from TTO	0.057	0.056	0.054
RMSD from TTO	0.072	0.071	0.069

Note: * statistically significant at 5% level.

Table 5 Method (5): DCE and TTO hybrid models

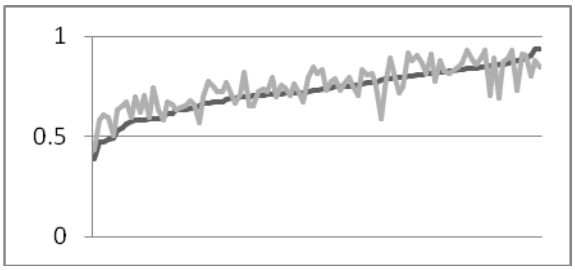
	Likelihood method			Bayesian method[1]		
	Method (5a) 10 states	Method (5b) 19 states	Method (5c) All states	Method (5a) 10 states	Method (5b) 19 states	Method (5c) All states
concern2	-0.008	-0.012	-0.023	0.008	0.003	-0.022
concern3	-0.029	-0.036	-0.029	-0.006	-0.010	-0.028
concern4	-0.069*	-0.070*	-0.064*	-0.052*	-0.056*	-0.069
concern5	-0.113*	-0.113*	-0.101*	-0.129*	-0.129*	-0.117
breath2	0.033	0.020	0.010	0.030	0.032	0.011*
breath3	-0.002	-0.008	-0.019	0.017	0.012	-0.016
breath4	-0.066*	-0.073*	-0.090*	-0.072*	-0.072*	-0.083
breath5	-0.092*	-0.100*	-0.094*	-0.081*	-0.089*	-0.100
pollution2	0.051	0.051	0.009	0.053*	0.058*	0.010*
pollution3	0.007	0.004	-0.023	-0.002	0.001	-0.027
pollution4	-0.034	-0.040*	-0.056*	-0.042*	-0.043*	-0.057
pollution5	-0.072*	-0.069*	-0.100*	-0.098*	-0.090*	-0.111
sleep2	-0.032	-0.033	-0.027	-0.022*	-0.017*	0.001*
sleep3	-0.053*	-0.052*	-0.048*	-0.068*	-0.059*	-0.046
sleep4	-0.102*	-0.096*	-0.085*	-0.118*	-0.110*	-0.081
sleep5	-0.106*	-0.100*	-0.105*	-0.124*	-0.114*	-0.097
activity2	-0.042*	-0.049*	-0.028	-0.027*	-0.039*	-0.035
activity3	-0.094*	-0.099*	-0.068*	-0.072*	-0.082*	-0.070
activity4	-0.171*	-0.180*	-0.167*	-0.209*	-0.209*	-0.185
activity5	-0.234*	-0.241*	-0.210*	-0.239*	-0.244*	-0.224
Teta	9.394	9.320	9.592	15.154	15.270	16.280
Number of observations	2055	2263	4015	2055	2263	4015
Inconsistencies	3	3	2	4	5	3
No. predictions >0.05 from observed TTO	48	50	43	56	51	46
No. predictions >0.1 from observed TTO	22	22	13	22	20	14
MAD	0.062	0.059	0.052	0.067	0.066	0.055
RMSD	0.080	0.067	0.067	0.084	0.083	0.070

Note: * statistically significant at 5% level.

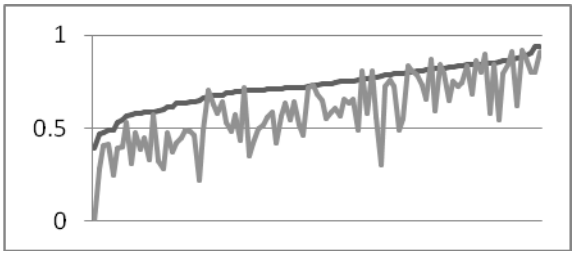
[1] Significance (*) has been generated using 95% credible intervals, where if the credible interval does not include zero the coefficient is deemed significant at the 5% level.

Figure 1 Predicted utility and observed TTO

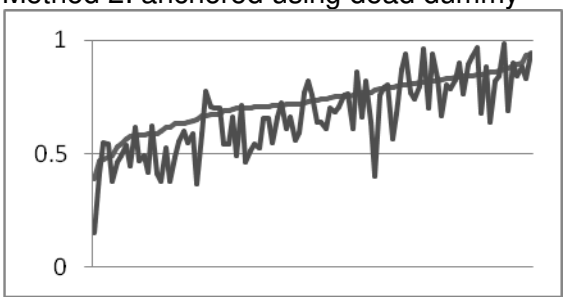
TTO estimates



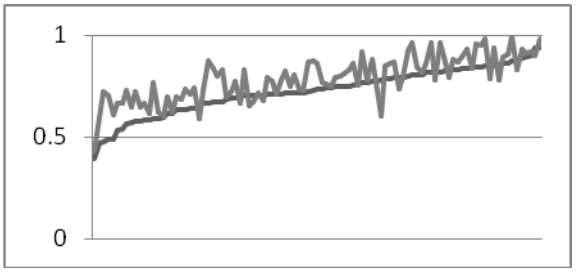
Method 1: anchored assuming worst state = zero



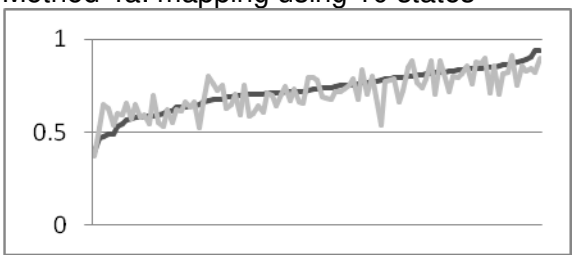
Method 2: anchored using dead dummy



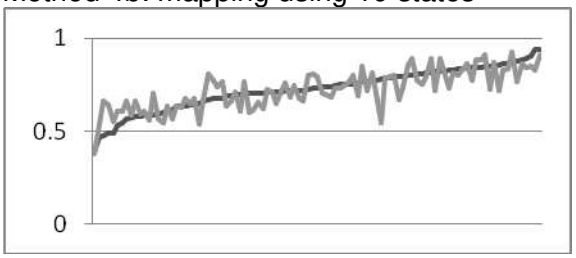
Method 3: anchored using worst state = TTO value



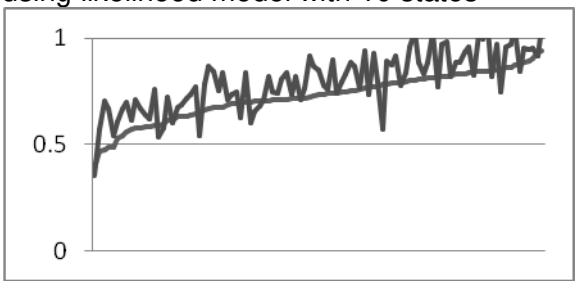
Method 4a: mapping using 10 states



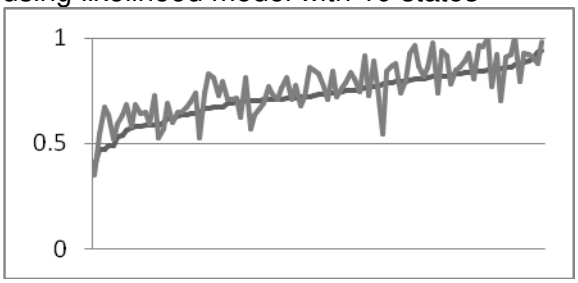
Method 4b: mapping using 19 states



Method 5a: DCE-TTO hybrid estimates using likelihood model with 10 states



Method 5b: DCE-TTO hybrid estimates using likelihood model with 19 states



Technical appendix

1) A combined likelihood function

We may combine the data from the TTO and DCE datasets as follows. For the linear regression part we assume a normal distributed error leading to:

$$v_i = \alpha + \sum_{j=1}^{nd} \beta_j d_{ij} + e_i = \alpha + \beta' d + e_i$$

$$e_i \sim N(0, \sigma^2)$$

This can be rewritten as:

$$f(v_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(- \frac{\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{2\sigma^2} \right)$$

and leading to the log likelihood function:

$$\text{loglik} = \log\left(\prod_{i=1}^{N} f(v_i) \right) = -\frac{N}{2}\log(2\pi) - \frac{N}{2}\log(\sigma^2) - \sum_{i=1}^{N} \frac{\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{2\sigma^2}$$

For the discrete choice data we may say:

$$P(left > right) = P(v_l) > P(v_r)$$

$$v_l = \sum_{j=1}^{nd} \beta_j d_{lj} + e_l; \quad v_r = \sum_{j=1}^{nd} \beta_j d_{rj} + e_r$$

$$P(left > right) == \frac{1}{\left(1 + \exp\left(- \sum_{j=1}^{nd} \beta_j \left(d_{lj} - d_{rj} \right) \right) \right)}$$

$$P(right > left) = \frac{\exp\left(- \sum_{j=1}^{nd} \beta_j \left(d_{lj} - d_{rj} \right) \right)}{\left(1 + \exp\left(- \sum_{j=1}^{nd} \beta_j \left(d_{lj} - d_{rj} \right) \right) \right)}$$

$$Loglik = \sum_{i=1}^{Npair} N^i_{LGTR} \log\left(\frac{1}{\left(1 + \exp\left(-\beta' \Delta d_i \right) \right)} \right) + \sum_{i=1}^{Npair} N^i_{RGTL} \log\left(\frac{\exp\left(-\beta' \Delta d_i \right)}{\left(1 + \exp\left(-\beta' \Delta d_i \right) \right)} \right)$$

The combination of the two may be seen as a simple product while acknowledging that they may differ up to a constant. The following likelihood was used to combine both sets of data:

$$\text{loglik} = -\frac{N}{2}\log(2\pi) - \frac{N}{2}\log(\sigma^2) - \sum_{i=1}^{N}\frac{\left(v_i - \sum_{j=1}^{nd}\beta_j d_{ij}\right)^2}{2\sigma^2} +$$

$$\sum_{i=1}^{Npair} N^i_{LGTR}\log\left(\frac{1}{(1+\exp(-\theta\beta'\Delta d_i))}\right) + \sum_{i=1}^{Npair} N^i_{RGTL}\log\left(\frac{\exp(-\theta\beta'\Delta d_i)}{(1+\exp(-\theta\beta'\Delta d_i))}\right)$$

b) A Bayesian approach

Methods 1-4 in the paper use random effects models and force the constant term to 1 (or zero). To compare these results to the results of hybrid method (5) we have to redefine the likelihoods, and here it is done using a Bayesian approach.

In the logistic model, used for the DCE data, we assume:

$$c_i^j \sim Bernouilli(p_i^j) \quad i = 1,..,N_{subjects}, \quad j = 1,...,N^i_{states}$$
$$\text{logit}\,(p_i^j) = \beta_i'\Delta d^j \quad i = 1,..,N_{subjects}, \quad j = 1,...,N^i_{states}$$
$$\beta_i \sim N(\bar{\beta},\delta) \quad i = 1,..,N_{subjects}$$

Here, c_j^i is the answer of individual *i* to a discrete choice *j* (between two states), Δd^j is a vector measuring the difference in the dummy variables that characterise the health states in comparison *j*. β_i is a subject specific vector of parameters weighing the differences between the health states. Finally, $\bar{\beta}$ is the vector of average weights which is the main focus here.

In the linear model used for the TTO data, where v_i^j is the TTO value given by individual *i* to state *j*, we assume:

$$v_i^j \sim N(\beta_i'\Delta d^j, \sigma^i) \quad i = 1,..,N_{subjects}, \quad j = 1,...,N^i_{states}$$
$$\beta_i \sim N(\bar{\beta},\delta) \quad i = 1,..,N_{subjects}$$
$$\sigma^i \sim \Gamma(g_1, g_2) \quad i = 1,..,N_{subjects}$$

In the hybrid approach we are using the same formulae as in the state approaches. However, we are saying that the mean beta's in both approaches are similar except for a constant ϑ. So, the whole model is now:

$$c_i^j \sim Bernouilli(p_i^j) \quad i = 1,..,N_{subjects}, \quad j = 1,...,N^i_{states}$$
$$\text{logit}\,(p_i^j) = \beta_i^{DCE}{}'\Delta d^j \quad i = 1,..,N^{DCE}_{subjects}, \quad j = 1,...,N^i_{states}$$
$$\beta_i^{DCE} \sim N(\bar{\beta}^{DCE},\delta) \quad i = 1,..,N^{DCE}_{subjects}$$
$$v_i^j \sim N(\beta_i^{TTO}{}'\Delta d^j, \sigma^i) \quad i = 1,..,N^{TTO}_{subjects}, \quad j = 1,...,N^i_{states}$$
$$\beta_i^{TTO} \sim N(\vartheta\bar{\beta}^{DCE},\delta) \quad i = 1,..,N^{TTO}_{subjects}$$
$$\sigma^i \sim \Gamma(g_1, g_2) \quad i = 1,..,N_{subjects}$$

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