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The University of Sheffield

May 2004

HEDS Discussion Paper 04/02

Sheffield Health Economics Group

Discussion Paper Series

May 2004

Ref: 04/2

Estimating population cardinal health state valuation models from individual ordinal (rank) health state preference data.

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Abstract

Ranking exercises have routinely been used as warm-up exercises within health state valuation surveys. Very little use has been made of the information obtained in this process. Instead, research has focussed upon the analysis of health state valuation data obtained using the visual analogue scale, standard gamble and time trade off methods.

Thurstone's law of comparative judgement postulates a stable relationship between ordinal and cardinal preferences, based upon the information provided by pairwise choices. McFadden proposed that this relationship could be modelled by estimating conditional logistic regression models where alternatives had been ranked. In this paper we report the estimation of such models for the Health Utilities Index Mark 2 and the SF-6D. The results are compared to the conventional regression models estimated from standard gamble data, and to the observed mean standard gamble health state valuations.

For both the HUI2 and the SF-6D, the models estimated using rank data are broadly comparable to the models estimated on standard gamble data and the predictive performance of these models is close to that of the standard gamble models. Our research indicates that rank data has the potential to provide useful insights into community health state preferences. However important questions remain.

Acknowledgement

Introduction

As cost effectiveness analysis has become more important in health care decision making processes, the interest in how to value health outcomes has increased. There is a substantial body of research on the relative strengths and weaknesses of alternative methods. [1][2][3][4] Such research has focused primarily on three valuation methods; Time Trade Off (TTO); Standard Gamble (SG); and Visual Analogue Scales (VAS), also called category scaling.

Work that has attempted to identify a preferred method has tended to support the use of TTO and/or SG. [5] VAS has been criticised on a number of points, both theoretical (does VAS capture strength of preference) and empirical (the data may be subject to end-point and context bias).[6] However, it is widely accepted that TTO and SG have significant limitations. What is remarkable is the degree to which the role of ordinal data in health state valuation has been largely ignored; notable exceptions to this observation being the work by Kind.[7][8]

Ranking exercises are conventionally included in health state valuation interviews as a warm-up exercise, in order to familiarise the interviewee with the health state classification system being valued and with the task of considering preferences between hypothetical health states.[9] The use of the data from these ranking exercises has generally been limited to checking the degree of consistency between the valuations obtained from the SG or TTO valuation exercises and the ranking exercise.

Kind identified Thurstone's model of comparative judgement as a potential theoretical basis for deriving cardinal preferences from rank preference data. Thurstone's

method considers the proportion of times that health state *A* is considered worse than health state *B*. The preferences over the health states represent 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. Therefore, choice data provide information about the cardinal latent utility function. McFadden proposed the conditional logistic regression model as a means of modelling this latent utility function from ordinal data.[10]

Recently Salomon presented work[11] that applied conditional logistic regression models to the rank data collected as part of the Measurement and Valuation of Health Study (MVH). Salomon estimated a model equivalent to that reported by Dolan.[12] This model did not produce utilities on the 0-1 scale necessary for use in estimating Quality Adjusted Life Years. Salomon rescaled the model coefficients on to the full health-death (1-0) scale, using the mean measured TTO value for the PITS state in the EQ-5D classification (3,3,3,3,3). In this paper we present an approach that avoids the need for external health state value data, as in such rescaling, by directly estimating a parameter for the state death, as part of the model. This method is applied to rank data from two health state valuation surveys; a UK based valuation survey for the Health Utilities Index Mark 2, [14] and the UK valuation survey for the SF-6D. [13]

Methods

Model specification

To model the predicted health state valuations using the ordinal preference data we used conditional logistic regression as outlined by McFadden. To operationalise this model we assumed that the ranking exercise is equivalent to the respondent making a series of individual selections from smaller and smaller groups. Thus, in ranking 10 health states we assume that the respondent first chooses the most preferred health state from all 10, before choosing the most preferred health state from the remaining 9 and so on, until all the health states have been assigned a rank between 1 and 10. To characterise this as equivalent to pair wise choice we must rely on the hypothesis of the Independence of Irrelevant Alternatives; i.e. the ranking of the pair is not affected by the other states that are ranked in the same exercise.

The conditional logistic regression model assumes that respondent i has a latent utility value for state j, U_{ij}, and that given the choice of two states j and k, the respondent will choose state j over state k if $U_{ij} > U_{ik}$. Hence given the task of choosing the preferred state from a finite group of different states, respondent i will choose state j if $U_{ij} > U_{ik}$ for all $j \neq k$.

Each individual's cardinal utility function for state j is $U_{ij} = \mu_j + \varepsilon_{ij}$ where μ_j is representative of the tastes of the population and ε_{ij} represents the particular taste of the individual. If the error term ε has an extreme value distribution, then the odds of choosing state j over state k are $exp\{\mu_j - \mu_k\}$.

For the analyses reported here, the expected value of each unobserved utility was assumed to be a linear function of the categorical levels on the dimensions of each dataset respectively. The general model specification is:

$$\mu_{ij} = g(\boldsymbol{\beta}'\mathbf{x_{ij}} + \theta D + u_{ij})$$

where μ = utility; i = 1, 2, …, n represents respondents and j = 1,2, …, m represents health states. g is a function specifying the appropriate functional form, which is assumed here to the linear. u_{ij} is an error term whose autocorrelation structure and distributional properties depend on the assumptions underlying the particular model used.

$\mathbf{x}$ is a vector of dummy explanatory variables ($x_{\lambda\delta}$) for each level λ of dimension δ of the instrument in question. For example for the SF-6D, x_{23} denotes dimension δ = 3 (social functioning), level λ = 2 (health limits social activities a little of the time). For any given health state, $x_{\lambda\delta}$ will be defined as

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

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

Level 1 is the baseline for each dimension.

D is a dummy variable for the state 'Death', which takes the value 1 for this health state. For all other health states the variable Death is always set at 0.

Rescaling model coefficients on to the death-full health (1-0) scale

The latent variable µ is not measured on the zero-one (death-full health) scale required for calculating QALYs. Therefore, we rescaled the coefficients using the formula $\beta_{r\lambda\delta} = \beta_{\lambda\delta} / \theta_D$; where $\beta_{r\lambda\delta}$ is the rescaled coefficient on dimension level $\lambda\delta$ and θ_D is the coefficient on death. These rescaled coefficients provide predictions for health state values on the same scale as SG or TTO valuations, although not necessarily the same values. This method of rescaling anchors death at zero and full health at 1, whilst retaining the possibility of a health state having a value of <0; i.e. worse than death.

Model Assessment

Models are assessed in a number of stages. The first stage checks that the estimated model coefficients have the expected negative sign and that they are statistically significant. These coefficients are then rescaled on to the full health-death (1-0) scale and the rescaled coefficients are checked for logical inconsistencies; i.e, that lower levels of functioning are associated with greater decrements in health state value.

The rescaled coefficients are then compared to the coefficients from the preferred models estimated on the SG data from the same valuation interviews.[14] We assessed the predictive performance of the models using the following battery of measures:

- Root Mean Square Error (RMSE),
- Mean Absolute Error (MAE),

- Proportion of health state values predicted to within 0.05 of the observed mean of the standard gamble valuations

- Ljung-Box test for autocorrelation in the errors[15]

In addition we plot the health state values predicted by the models against the observed mean SG values and the values predicted by the original SG models. We also plot the errors against the observed mean values. We use the Hausman test to test the validity of the Independence of Irrelevant Alternatives assumption (IIA).[16]

We report model coefficients, significance levels, diagnostic plots and tests of predictive performance for both the HUI2 and the SF6D models.

Surveys

Descriptions of both of these valuation surveys have been reported in detail elsewhere, thus, we will only provide a brief summary of them here.

Health Utilities Index Mark 2

The Health Utilities Index Mark 2 is a six dimension health state classification (sensation, mobility, emotion, cognition, self care and pain) with either four or five levels for each dimension. It describes a total of 8,000 distinct health states. It was developed specifically for use with paediatric populations.[17] (See Appendix 1)

One hundred and ninety eight respondents ranked 8 health states from the HUI2 classification plus Full Health and Immediate Death. The health states valued were sampled from an orthogonal array for the HUI2 classification. The interviewees then

valued the same 8 health states using the McMaster version of the SG question; i.e. the chance board prop was used to aid the respondent in understanding the question. The risk of death was varied in a ping-pong manner until the interviewee identified a risk of death at which they were indifferent between the impaired health state and the uncertain choice. Where health states were ranked as worse than immediate death, the worse than death version of the SG question was used.

The respondent was asked to imagine that they were a ten year old child who would live for another 60 years in the outcome health state.

SF-6D

The SF-6D has 6 dimensions: physical functioning, role Limitations, social functioning, pain, mental health and vitality. Each dimension has 4,5 or 6 levels. The classification describes a total of 18,000 health states. (See Appendix 2)

A representative sample of 611 members of the UK population provided standard gamble valuations for a sample of 249 health states defined by the SF-6D classification.

The interview consisted of an exercise to rank 5 health states that the respondent would then be asked to value, plus the best and worst states defined by the SF-6D and immediate death. This was followed by a series of SG questions. The SG question asked the respondent to value one of 5 certain SF-6D health states against the best and 'pits' health state. All respondents were then asked to provide a SG valuation of the PITS state in relation to death. The form of the sixth SG valuation depended upon whether the respondent has ranked the PITS state as better or

worse than death, in the ranking exercise. The result of the sixth SG exercise was then used to 'chain' the health state values in order to place them on to the 1-0, full health –death scale. The interviewers used the McMaster chance board prop and the ping-pong version of the SG question.

The respondent was asked to answer the question for him or herself, imagining that they would remain in the outcome health state for the rest of their lives.[18]

Results

Health Utilities Index Mark 2

Table 1 reports the original and rescaled coefficients for the rank health state value models for the HUI2. It also gives the results for each of the diagnostic tests. For comparative purposes the same information is provided for the SG health state valuation model.

The similarity of the rank and SG data models is quite striking. The rank model has one more inconsistency than the SG model, and does not distinguish as clearly between the different levels on the mobility dimension. However, this dimension is one of the weaker dimensions in the SG model. With the exception of the sensation and mobility, the utility decrement for the impaired levels of functioning on each dimension are larger in the SG than the rank model. The predictive performance of the two models is closer than we would have expected given the difference in the level of information the two models were estimated from. This said, the SG model does perform better than the rank model on all tests.

Figure 1 plots the observed health state values and the prediction errors for both the SG and the rank health state models. The plots confirm the similarity of the predictive performance of the rank and SG models.

SF-6D

Table 2 reports the same information for the SF-6D models.

The rank data model is quite different from the SG model. It is notable that the number of inconsistencies is lower in the rank data model than the SG model. Whilst there are inconsistencies in the coefficients for role physical, in both models, there are fewer in the rank model than the SG model. The vitality dimension in the SG model has a number of inconsistencies, the rank model by contrast has none. The predictive performance of the rank model is slightly worse than the SG model, for most tests. However, this may not be surprising as the SG model is being used to

estimate the data on which it was estimated, whilst the rank model is being used to estimate a different dataset, although the data was obtained from the same sample of respondents. The LB test results suggest that the relationship between prediction error and observed health state value is less strong for the rank model than the SG model.

Figure 2 plots the observed mean values and the prediction errors for both the SG and rank data models. It is clear that there is greater variability in the errors for the SF-6D compared with the HUI2.

Independence of Irrelevant Alternatives

Table 3 reports the test of the assumption of Independence of Irrelevant Alternatives for both the HUI2 and SF-6D rank models. The results are not consistent across all the rank groups, but for both the HUI2 and the SF-6D models, there is evidence that this assumption does not hold. The models appear to be most sensitive to the exclusion of those states ranked highly or lowly.

Discussion

In this paper we have reported the estimation of population cardinal health state valuation models for the HUI2 and the SF-6D, from individual ordinal preference data. In both cases the models bare comparison to the health state valuation models estimated from SG (cardinal) data provided by the same respondents.

The impetus for this research was an analysis of rank data for the EQ-5D, presented by Salomon. It is notable that the degree of agreement between the rank model and the TTO model for the EQ-5D is considerably less than we report for the rank and SG models we have estimated.

Our apparent success in estimating cardinal health state valuation models from ordinal data raises many questions. In describing our results as a success, we are assuming that the SG data are the appropriate 'gold standard' by which to judge these models. It is arguable that our results say as much about the limitations of SG

data as they do about the existence or otherwise of a latent utility function. Research is required to examine whether respondents expressed preferences are consistent with the models that are derived from the SG (and TTO) values they provide. Such work is likely to require qualitative as well as quantitative methods.

Our analysis of the performance of the rank models has assumed that the relationship between the observed SG values and the predictions of the rank models is linear. There is no reason why this should be so. The ranking exercise does not involve risk, whilst the SG explicitly incorporates risk into the valuation process. Standard models of risk attitude would suggest that a linear model would not be the best functional form.[19] Future work should look at the performance of alternative functional forms. Theoretical perspectives on the relationship between rank and SG data should inform such research.

The application of the conditional logistic regression model requires that the rank data exercise be characterised as a sequential choice process. Whilst we believe that this assumption is defensible, we accept that other models of the ranking process are equally plausible. The results of the Hausman test results suggest that this assumption may not be robust and therefore our results must be treated with some caution. There is an increasing body of research suggesting that respondents apply decision heuristics to complex choice scenarios, and that lexicographic preferences are common in contingent valuation studies. Research on the thought processes of individual's undertaking ranking exercises would be a valuable contribution to this field.

A potential solution to this problem would be to design the ranking exercise to ensure consistency with the underlying assumptions of the model. Thus the respondent would be presented with all the health states to be ranked and asked to identify the highest ranked health state. This would be recorded and then the respondent would be presented with the remaining health states and again asked to identify the highest ranked health state from that set. This process would be repeated until all the states had been ranked. Work to establish the feasibility of undertaking this type of valuation exercise and to compare the results with those from the ranking exercises presented here would be of significant value.

Our analyses assume that the rank data are preference data. The literature on health state preference elicitation has generally argued that VAS data are not preferences

because the valuation process does not require the respondent to trade. This same observation can be applied to ranking exercises. If rank data are reflecting an underlying utility function the utility functions may reflect Broome's concept of the relative 'goodness' of different health states, rather than the conventional expected utility, that the SG is designed to measure.[20]

The analyses assume that the information content of the rank is unaffected by the order of the rank or indeed the number of states to be ranked. Hausman and Ruud have hypothesised that respondents may take more care with the initial ranking exercises than the later ones.[21] Thus the risk of a ranking being incorrect would be systematically related to a health state's position in the rank; i.e. the assumption of independence of irrelevant alternatives would not hold. Koop and Poirier report that a limited relaxation of this assumption in a model of voter preferences did not have a significant impact upon the results.[22] Our results suggest that the assumption does not hold for either model, and that the models are sensitive to both the highly ranked and lower ranked health states, but relatively insensitive to those states ranked in the middle.

Should future research confirm the promise of ordinal data to support the modelling of cardinal health state preferences, it is by no means clear what the implications for future health state valuation work would be. It may be that ranking data may make it possible to incorporate the views of populations for whom the TTO and SG procedures are felt to be too arduous e.g. younger children.[23] However, the ranking tasks themselves are not simple and no research to date has examined children's ability to understand them.

An alternative benefit may be that the future valuation surveys may require fewer resources. In addition, ranking exercises may be more feasible in postal interviews than TTO and SG, again allowing more efficient implementation of health state valuation surveys. It might be that rank data offers the convenience of the VAS without the problems of context and end-point bias.

These results raise questions about the relationship between discrete choice experiments and the conventional methods of obtaining health state preferences for calculating QALYs. The format of the discrete choice question fits more immediately within the comparative judgement framework than the

ranking exercises described above. It seems reasonable to expect that discrete choice scenarios that included a dimension for mortality (or risk of mortality) might be suitable data sources for a similar modelling strategy to that described in this paper.

Summary

In this paper we have presented two models of population cardinal health state preferences based upon individual ordinal health state preference data; one for the SF-6D health state classification, the other for the HUI2 health state classification. We have compared these to models estimated on SG valuation data, in terms of the degree of accuracy and bias in predicting mean observed SG health state valuations in the estimation samples.

The ordinal rank models perform much better than might have been expected given the difference in the informational content between the SG and ranking exercises.

The results are consistent with Thurstone's law of comparative judgement, and the existence of a latent utility function. The results also suggest that there is potential for discrete choice experiments to provide health state preference data on the full health-death scale. Further research on the potential for ordinal health state valuation data to reflect cardinal population preferences is required.

Table 1: Ordinal and Standard Gamble Health State Valuation Models for HUI2[1]

	RankCoeff	RescaledCoeff	SGCoeff
sens2	-0.9933	-0.1156	-0.1151
sens3	-0.9351	-0.1089	-0.1223
sens4	-2.1167	-0.2464	-0.2253
mobil2	-0.7287	-0.0848	-0.0516
mobil3	-0.9887	-0.1151	-0.1224
mobil4	-0.8041	-0.0936	-0.1308
mobil5	-1.0085	-0.1174	-0.1103
emot2	-0.8122	-0.0946	-0.0945
emot3	-1.0001	-0.1164	-0.1119
emot4	-1.4291	-0.1664	-0.1801
emot5	-1.4378	-0.1674	-0.1824
cogn2	-0.3223	-0.0375	-0.0567
cogn3	-0.5438	-0.0633	-0.0966
cogn4	-0.7732	-0.0900	-0.1676
sc2	-0.4409	-0.0513	-0.0516
sc3	-0.6924	-0.0806	-0.1138
sc4	-0.7762	-0.0904	-0.1158
pain2	-0.8132	-0.0947	-0.1114
pain3	-0.9401	-0.1095	-0.1155
pain4	-1.2169	-0.1417	-0.1626
pain5	-1.7654	-0.2055	-0.2538
death	-8.5895	-1	
n states		51	51
MAE		0.062	0.051
No.>0.05		23	18
No.>0.10		12	5
RMSE		0.0775	0.0657
LB		36.11	25.78
Corr(means)		0.8814	0.921
No. of Logical Inconsistencies		2	1

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[1] All coefficients for both models were significant at the p<0.1.

Table 2: Ordinal and Standard Gamble Health State Valuation Models for SF-6D[2]

	RankCoeff	RescaledCoeff	SGCoeff
pf2	**-0.3636**	**-0.0566**	**-0.0600**
pf3	**-0.4313**	**-0.0671**	-0.0200
pf4	**-0.9856**	**-0.1534**	**-0.0600**
pf5	**-0.6340**	**-0.0987**	**-0.0630**
pf6	**-1.4475**	**-0.2253**	**-0.1310**
rl2	**-0.3211**	**-0.0500**	**-0.0570**
rl3	**-0.4069**	**-0.0633**	**-0.0680**
rl4	**-0.4053**	**-0.0631**	**-0.0660**
sf2	**-0.3627**	**-0.0565**	**-0.0710**
sf3	**-0.4203**	**-0.0654**	**-0.0840**
sf4	**-0.5737**	**-0.0893**	**-0.0930**
sf5	**-0.8055**	**-0.1254**	**-0.1050**
pain2	**-0.3772**	**-0.0587**	**-0.0480**
pain3	**-0.3635**	**-0.0566**	-0.0340
pain4	**-0.6520**	**-0.1015**	**-0.0700**
pain5	**-0.8187**	**-0.1275**	**-0.1070**
pain6	**-1.1912**	**-0.1854**	**-0.1810**
mh2	**-0.2157**	**-0.0336**	**-0.0570**
mh3	**-0.3371**	**-0.0525**	**-0.0510**
mh4	**-0.7016**	**-0.1092**	**-0.1210**
mh5	**-0.8993**	**-0.1400**	**-0.1400**
vit2	**-0.1740**	**-0.0271**	**-0.0940**
vit3	**-0.2140**	**-0.0333**	**-0.0690**
vit4	**-0.3226**	**-0.0502**	**-0.0690**
vit5	**-0.5267**	**-0.0820**	**-0.1060**
death	**-6.4240**	**-1.0000**	
n states		249	249
MAE		0.088	0.074
No.>0.05		169	118
No.>0.10		84	52
RMSE		0.110	0.098
LB		106.720	169.570
Corr(means)		0.7111	0.7377
No. of logical inconsistencies		3	5

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[2] Coefficients in bold are significant at p<0.1

Table 3: Hausman's Test for Independence of Irrelevant Alternatives

Health Utilities Index Mark 2				SF-6D		
Category	Hausman	p		Category	Hausman	p
3	80.39	0.0000		8	126.03	0.0000
7	49.56	0.0007		6	35.2	0.1074
8	15.91	0.8202		.	24.03	0.5741
9	21.14	0.5119		7	30.62	0.2426
2	20.71	0.5388		4	32.32	0.1828
4	26.49	0.2311		5	75.53	0.0000
10	50.64	0.0005		3	110.45	0.0000
5	190.44	0.0000		2	221.1	0.0000
6	221.3	0.0000		-	-	-
1	-299.42	1.0000		-	-	-

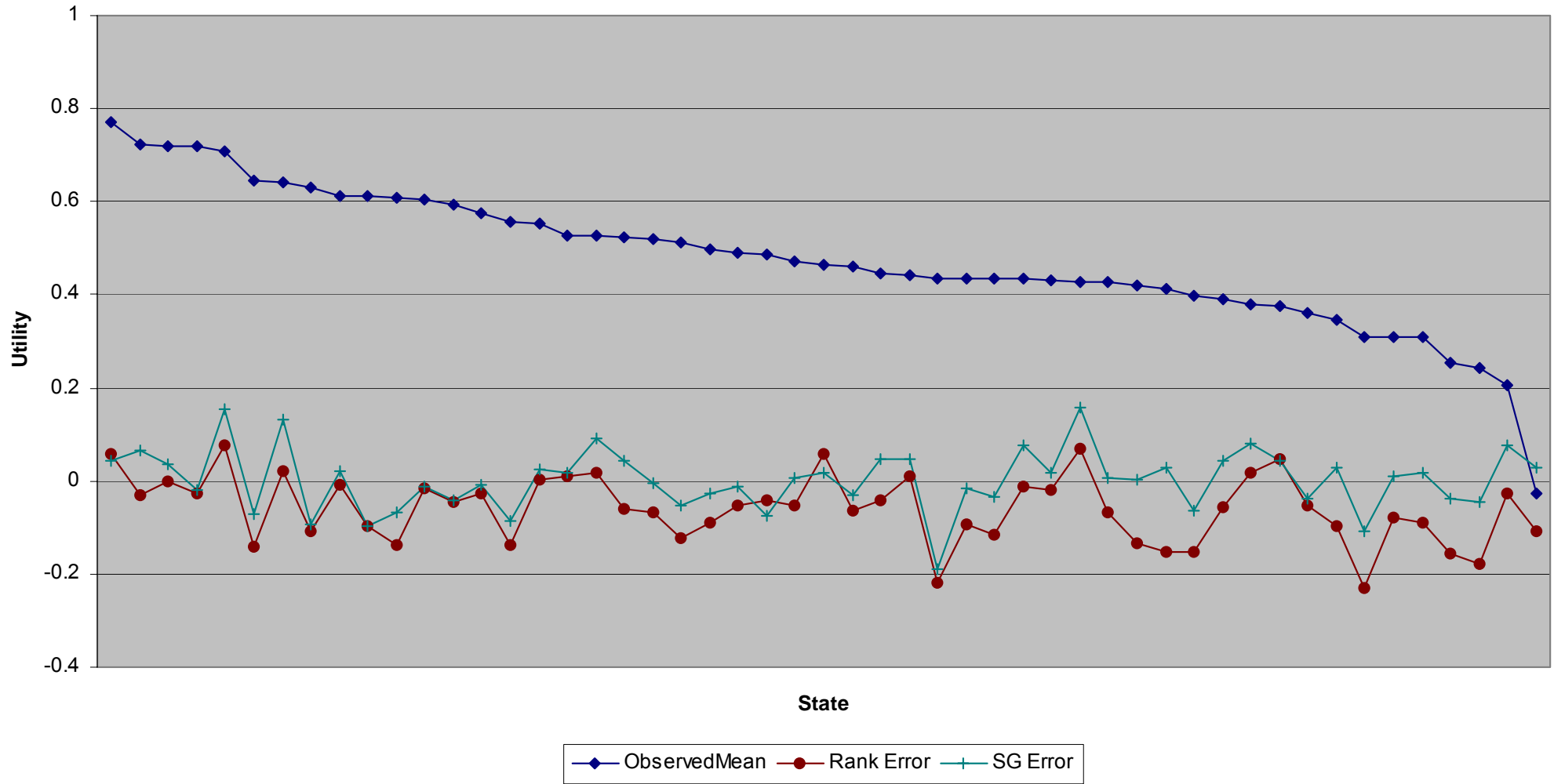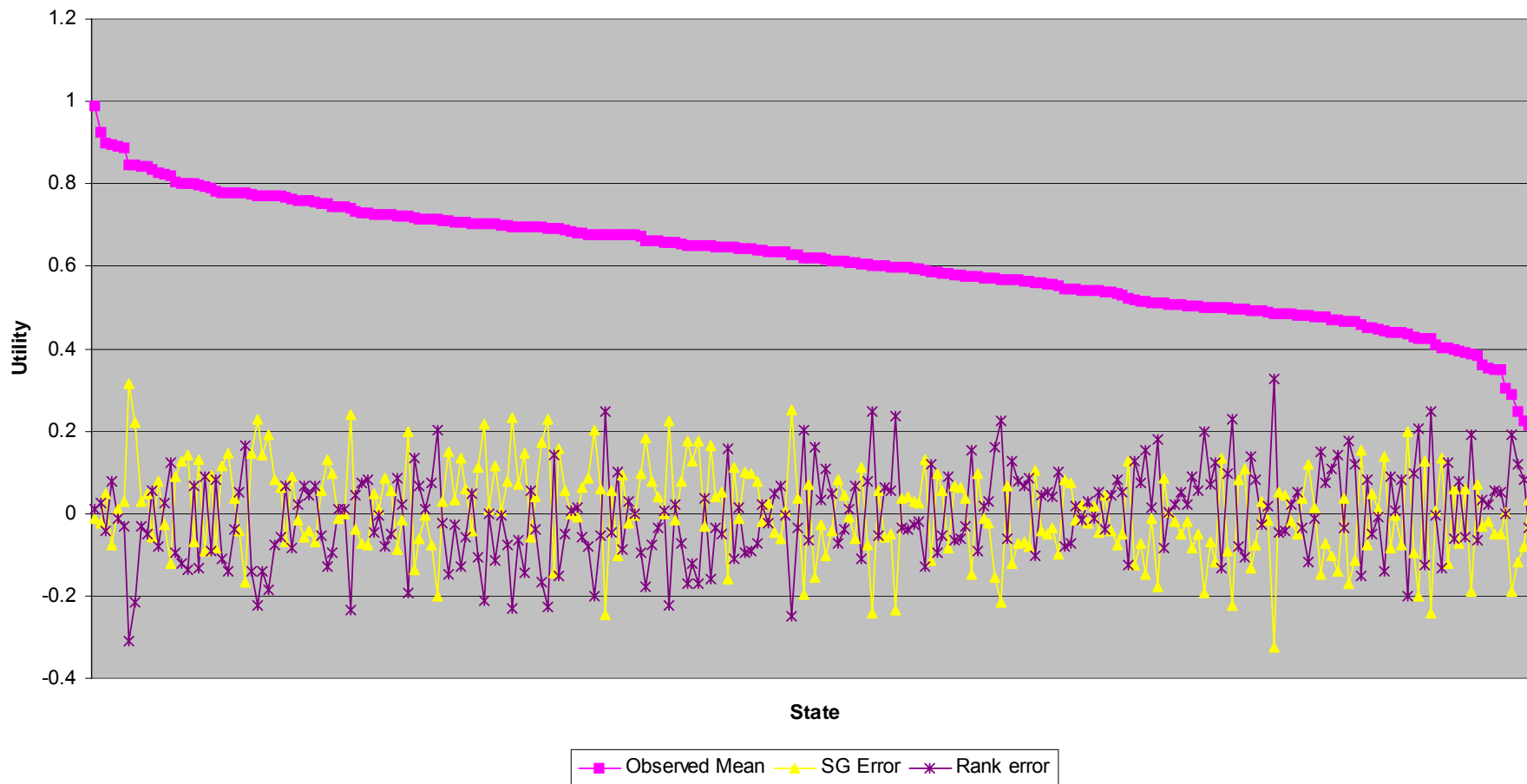Figure 1: Prediction Errors for SG and Rank Models: HUI2

Figure 2: Prediction Errors for SG and Rank models: Sf-6D

Appendix 1: Health Utilities Index Mark 2

Level	**Sensation**
1	Able to see, hear and speak normally for age
2	Requires equipment to see or hear or speak
3	Sees, hears, or speaks with limitations even with equipment
4	Blind, deaf, or mute

Level	**Self care**
1	Eats, bathes, dresses and uses the toilet normally for age
2	Eats, bathes, dresses or uses the toilet independently with difficulty
3	Requires mechanical equipment to eat, bathe, dress, or use the toilet independently
4	Requires the help of another person to eat, bathe, dress or use the toilet

	Mobility
1	Able to walk, bend, lift, jump and run normally for age
2	Walks, bends, lifts, jumps or runs with difficulty but does not require help
3	Requires mechanical equipment (such as canes, crutches, braces or a wheelchair) to walk or get around independently
4	Requires the help of another person to walk or get around and requires mechanical equipment
5	Unable to control or use arms or legs

	Cognition
1	Learns and remembers schoolwork normally for age
2	Learns and remembers schoolwork more slowly than classmates as judged by parents and/or teachers
3	Learns and remembers very slowly and usually requires special educational assistance
4	Unable to learn and remember

	Emotion
1	Generally happy and free from worry
2	Occasionally fretful, angry, irritable, anxious depressed or suffering from "night terrors"
3	Often fretful, angry, irritable, anxious depressed or suffering from "night terrors"
4	Almost always fretful, angry, irritable, anxious, depressed
5	Extremely fretful, angry, irritable, anxious or depressed usually requiring hospitalisation usually requiring hospitalisation or psychiatric institutional care

Pain

1	Free of pain and discomfort
2	Occasional pain. Discomfort relieved by non-prescription drugs or self-control activity without disruption of normal activities
3	Frequent pain. Discomfort relieved by oral medicines with occasional disruption of normal activities
4	Frequent pain. Frequent disruption of normal activities. Discomfort requires prescription narcotics for relief
5	Severe pain. Pain not relieved by drugs and constantly disrupts normal activities.

Appendix 2: The Short Form 6D

Level	**Physical Functioning**
1	Your health does not limit you in <u>vigorous activities</u>
2	Your health limits you a little in <u>vigorous activities</u>
3	Your health limits you a little in <u>moderate activities</u>
4	Your health limits you a lot in <u>moderate activities</u>
5	Your health limits you <u>a little in bathing and dressing</u>
6	Your health limits you <u>a lot in bathing and dressing</u>

Level	**Pain**
1	You have <u>no</u> pain
2	You have pain but it does not interfere with your normal work (both outside the home and housework)
3	You have pain that interferes with your normal work (both outside the home and housework) <u>a little bit</u>
4	You have pain that interferes with your normal work (both outside the home and housework) <u>moderately</u>
5	You have pain that interferes with your normal work (both outside the home and housework) <u>quite a bit</u>
6	You have pain that interferes with your normal work (both outside the home and housework) <u>extremely</u>

	Role limitations
1	You have <u>no</u> problems with your work or other regular daily activities as a result of your physical health or any emotional problems
2	You are limited in the kind of work or other activities as a result of your physical health
3	You accomplish less than you would like as a result of emotional problems
4	You are limited in the kind of work or other activities as a result of your physical health and accomplish less than you would like as a result of emotional problems

	Mental health
1	You feel tense or downhearted and low <u>none of the time</u>
2	You feel tense or downhearted and low <u>a little of the time</u>
3	You feel tense or downhearted and low <u>some of the time</u>
4	You feel tense or downhearted and low <u>most of the time</u>
5	You feel tense or downhearted and low <u>all of the time</u>

	Social functioning
1	Your health limits your social activities <u>none of the time</u>
2	Your health limits your social activities <u>a little of the time</u>
3	Your health limits your social activities <u>some of the time</u>
4	Your health limits your social activities <u>most of the time</u>
5	Your health limits your social activities <u>all of the time</u>

	Vitality
1	You have a lot of energy <u>all of the time</u>
2	You have a lot of energy <u>most of the time</u>
3	You have a lot of energy <u>some of the time</u>
4	You have a lot of energy <u>a little of the time</u>
5	You have a lot of energy <u>none of the time</u>

Footnote: The SF-36 items used to construct the SF-6D are as follows: physical functioning items1, 2 and 10; role limitation due to physical problems item 3; role limitation due to emotional problems item 2; social functioning item 2; both bodily pain items; mental health items 1 (alternate version) and 4; and vitality item 2.

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