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Modeling EQ-5D-5L valuation data

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INTRODUCTION

With the increase from 3 to 5 levels, the number of possible health states described by the EQ-5D will increase from 243 to 3125 and new valuation studies are needed to obtain values for all those health states. After recognizing that TTO as an elicitation technique has its limitations it has been realized that other techniques might be needed to replace or be used in conjunction with TTO to make the valuation studies more affordable and feasible. One possible technique is the Discrete Choice modeling (DC). In 2008 a pilot study was undertaken in the Netherlands by members of the valuation taskforce of the EuroQol Group on the use of DCM for valuation of the EQ-5D-3L[1]. This 3L pilot study comprised a systematic comparison of Ranks and VAS, TTO, and DC derived values for EQ-5D health states in order to investigate whether or not modeling DC data produces health state values that are comparable to other conventional valuation techniques, TTO in particular. It was found that DC values broadly replicated the pattern found in TTO responses, although the DC values were consistently higher than TTO values. Therefore the valuation taskforce of the EuroQol Group explored the possibility of combining the TTO and DC data into a single modeling framework.

The first set of pilot studies undertaken to develop the valuation protocol for the EQ-5D-5L using TTO and DC was undertaken in the first half of 2011. Alongside those studies a number of modeling techniques were developed and tested but because of many imperfections in the TTO data collected in those studies, it was not possible to investigate the issues related to the simultaneous modeling of both DCE and TTO data. However, recently the first “real” valuation study using the new EQ-5D-5L valuation technology (EQ-VT) in Spain has been completed[2,3] which has renewed the need for a reconsideration of the issues around the modeling of valuation data.

The aim of this paper is to identify and describe the issues related to modeling the valuation data of the EQ-5D-5L, and to illustrate these based on analyses using the Spanish EQ-VT data. The issues can broadly be divided in two sets: core questions,

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and secondary issues. We've identified the following four issues as the core issues to solve for deciding on the best modeling method and structure for the valuation data obtained with the new EuroQol Valuation Technology EQ-VT.

Core Issues:

(i) Which type of data should be used to obtain the valuation models for EQ-5D-5L: Time Trade Off (TTO), Discrete Choice (DC), or both?
(ii) Which model specification should be used to model the main effects: do we continue with dummy models or are there better alternatives?
(iii) How should interaction be addressed? As diminishing misery (i.e. similar to the N3 term of the 3L models) or as "true" interactions
(iv) The lowest possible value in the LT-TTO, when the lead time is exhausted, is -1. What is the impact of modeling lead time exhaustion as a censoring event thereby removing the floor effect?

The first issue is on the selection of the method for data elicitation in the EQ-VT, which captures both TTO data and DC data. The second and third issues both have to do with the question of how to obtain the most parsimonious model. In addition to these core issues, we also wanted to address a number of secondary issues that we think are important (or at the very least interesting) for the modelling of the EQ-VT data. We've identified the following six issues as the secondary issues to solve for deciding on the best modelling method and structure for the valuation data obtained with the new EuroQol Valuation Technology EQ-VT.

Secondary Issues:

(i) Since not all respondents use the same heuristics when valuing health states, can we identify groups of respondents who use the same heuristics and model them separately?
(ii) Should we use random coefficient models on EQ-VT data?
(iii) Should we use the mean or the median as a measure of central tendency in composite TTO data?
(iv) How does the precision of the answers relate to the speed of iteration required to obtain those answers
(v) Can we address the issue of heteroscedasticity in the EQ-VT data (e.g. floor and ceiling effect) with beta regression?
(vi) Should we exclude respondents and by which criteria?

The first three of these secondary issues are related to how we should interpret the data we use to model with. The last three issues address more advanced types of models and exclusion of respondents. The secondary issues we highlight in this paper equally apply to the EQ-5D-3L.

The structure of this paper is as follows. We start by thoroughly describing both the TTO and the DC data. This is then followed by addressing the issues identified in this paper and a discussion. We do not present any firm recommendations and we do not want to claim that we are presenting all potential issues, let alone that we present all potential solutions. The paper is a sketch of where we are at this moment. We hope that we will be much further at the moment that this paper is being discussed.

5.1 DESCRIPTION OF THE EQ-VT DATA

To illustrate the issues and the thoughts underlying them, we used data from a sample of N=986 respondents from Spain. Each respondent valued a set of 10 EQ-5D-5L states using the composite TTO. After that, the respondents were asked to answer 7 paired comparisons in the DC task. A total of 86 states were included in the design for the composite TTO valuation task. These 86 states were divided over 10 blocks in such a way that each block had at least one of the 5 very mild states and 55555. The DC task had a design of 196 pairs divided over 28 blocks.

Composite TTO

Because the number of states that are included in the EQ-VT is so high relevant details of the data: the number of observations per state and mean values; histograms of the distributions of the composite TTO data; and charts with iterative paths taken by the respondents are presented in Appendix 5A. The histograms show that the TTO data look nice (for TTO data), with the distribution changing from clusters of data at the upper end of the scale for the mild states to clusters around 0 and -1 for the extreme states. The charts showing the iterative paths indicate that overall, the respondents did not shortcut the task.

Figure 5.1 shows the mean observed utilities for all 86 health states included in the EQ-VT, while Figure 5.2 shows the mean observed TTO utility values by severity score of the EQ-5D-5L (i.e. the sum score of the health state levels). As can be seen from these figures, the 86 states are nicely spread out over the utility scale and the relation between utilities and severity score is as expected (i.e. higher severity leads to lower utility).

In order to get more of a feel for the data we also fitted some elementary models to crudely map out the structure of the underlying data: an OLS model with 5 parameters (1 for each dimension) and an OLS model with 20 parameters (4 dummies per dimension). Both models perform roughly equally well with R^2 = 0.267 and 0.272 respectively, see Figure 5.3.

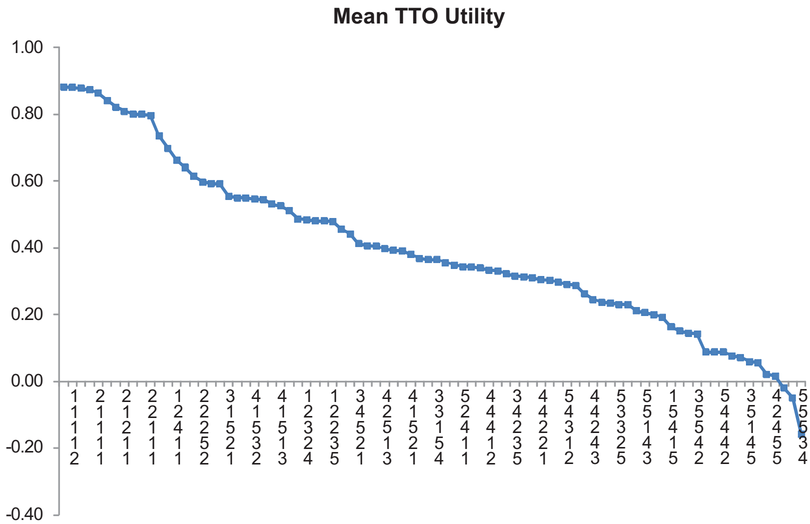

Figure 5.1 Mean observed utilities for all 86 health states included in the EQ-VT

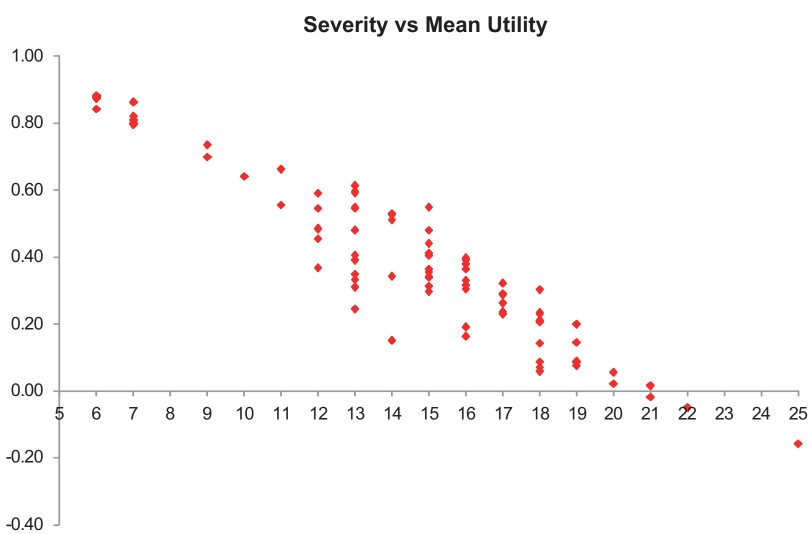

Figure 5.2 Mean TTO utility versus severity score

As can be seen in Table 5.1, all coefficients have the correct sign. Furthermore the weights for mobility pain and anxiety are higher than for self care and usual activity, which is consistent with the 3 level instrument. The parameter estimate for mobility level 2 was not significant and the estimates for usual activity level 4 and 5 are in reversed order in the 20 parameter model.

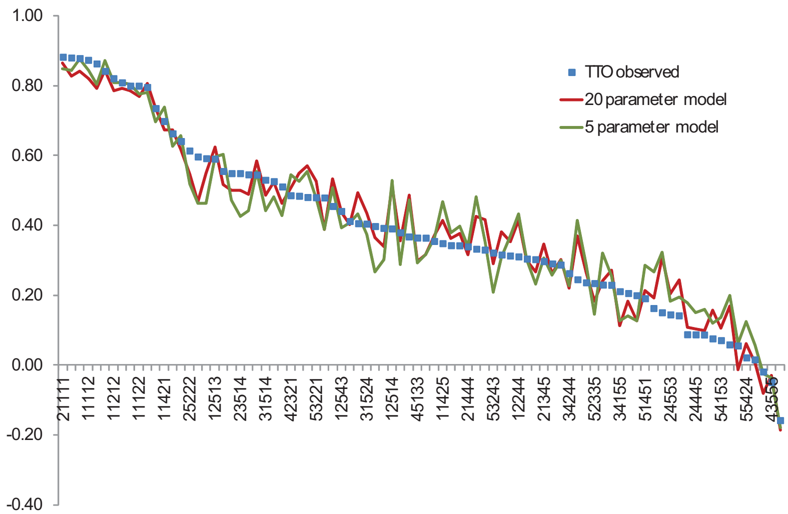

Figure 5.3 Mean observed versus predicted TTO values for the 86 states in the EQ-VT

Table 5.1 Basic OLS models for the Composite TTO

5 parameter model				20 parameter model			
Parameter	estimate	SE	p-value	Parameter	estimate	SE	p-value
Constant	1.184	0.015	.000	Constant	-0.122	0.018	.000
MO	-0.063	0.004	.000	MO2	-0.014	0.017	.405
				MO3	-0.065	0.017	.000
				MO4	-0.213	0.019	.000
				MO5	-0.231	0.018	.000
SC	0.040	0.004	.000	SC2	-0.035	0.016	.032
				SC3	-0.035	0.019	.065
				SC4	-0.162	0.018	.000
				SC5	-0.173	0.017	.000
UA	-0.035	0.004	.000	UA2	-0.036	0.017	.038
				UA3	-0.071	0.018	.000
				UA4	-0.153	0.018	.000
				UA5	-0.120	0.017	.000
PD	-0.067	0.004	.000	PD2	-0.051	0.016	.001
				PD3	-0.096	0.019	.000
				PD4	-0.186	0.016	.000
				PD5	-0.280	0.018	.000
AD	-0.067	0.004	.000	AD2	-0.057	0.017	.001
				AD3	-0.099	0.019	.000
				AD4	-0.208	0.018	.000
				AD5	-0.260	0.017	.000

Discrete Choice

A table with an overview with the observations per pair and the observed choice probabilities is presented in Appendix 5B. There are four pairs where all the respondents agreed on the answer, implying a choice probability of 100% versus 0%. A further 7 pairs have only one observation in either of the states leading to a choice probability of 97% versus 3%.

The same 5 parameter model and 20 parameter model were fitted on the DC data using a conditional logit model. Both models fit almost equally well with pseudo $R^2 = 0.228$ and 0.243. The model fit is illustrated in Figure 5.4, which shows the observed versus predicted choice probabilities for state A from the 20 parameter model.

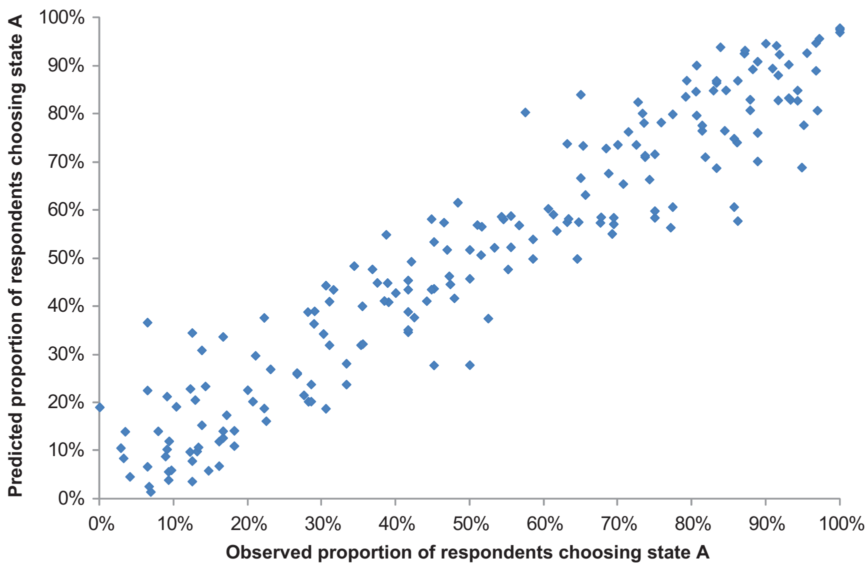

Figure 5.4 Observed versus predicted choice probabilities for the 20 parameter model

The model parameters are shown in Table 5.2. As can be seen in this table, all coefficients have the correct sign. Again, the weights for mobility, pain and anxiety are higher than for self care and usual activity. The parameter estimates for usual activity level 2 and 3 are in reversed order in the 20 parameter model.

In order to assess the impact of the 11 pairs with extreme choice probabilities we also fitted the 20 parameter model on the reduced set of 185 pairs. As can be seen in Figure 5.5 this has little impact on the model.

Table 5.2 Basic conditional logit models for the Discrete Choice

5 parameter model				20 parameter model			
Parameter	estimate	SE	p-value	Parameter	estimate	SE	p-value
MO	-0.383	0.017	.000	MO2	-0.476	0.058	.000
				MO3	-0.555	0.067	.000
				MO4	-1.178	0.067	.000
				MO5	-1.613	0.076	.000
SC	-0.204	0.014	.000	SC2	-0.171	0.063	.006
				SC3	-0.289	0.070	.000
				SC4	-0.722	0.069	.000
				SC5	-0.848	0.066	.000
UA	-0.172	0.015	.000	UA2	-0.213	0.060	.000
				UA3	-0.166	0.067	.013
				UA4	-0.560	0.066	.000
				UA5	-0.687	0.068	.000
PD	-0.464	0.016	.000	PD2	-0.376	0.064	.000
				PD3	-0.480	0.067	.000
				PD4	-1.213	0.069	.000
				PD5	-1.880	0.074	.000
AD	-0.442	0.016	.000	AD2	-0.361	0.066	.000
				AD3	-0.643	0.068	.000
				AD4	-1.315	0.074	.000
				AD5	-1.685	0.076	.000

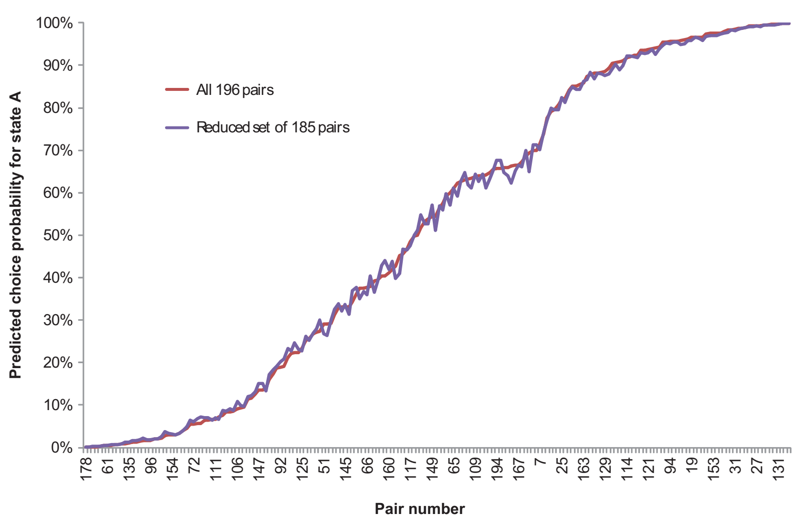

Figure 5.5 Impact of removing pairs with extreme choice probabilities (i.e. 100% vs 0% and 97% vs 3%) from the data on the model predictions of the 20 parameter model

5.2 CORE ISSUE 1

Which type of data should be used to obtain the valuation models for EQ-5D-5L: Time Trade Off (TTO), Discrete Choice (DC), or both?

The Spanish data shows that it is possible that both the TTO data and the DC choice data obtained with the EQ-VT are of good quality. This is made especially apparent from the results of estimating the most rudimentary models on both types of data and obtaining logical and consistent estimates for almost all parameters. This shows that both types of data are in principle suited for modelling EQ-5D-5L value sets.

There are several methods which enable the combination of both sets of data. Here we present some results using a likelihood approach. It builds on the notion that both (generalized) linear regression (as applied to the TTO data) as well as probit or logistic regression (as applied to the DCE data) can be obtained by maximum likelihood and that in general, they both contain a similar linear component $x'\beta$ underlying the values and choices[4]. Now one may assume that this component, which reflects the weight given to the dimensions and labels, is identical between both approaches and one may find the optimal parameters within this by creating just one likelihood function which is the product of the likelihood of the TTO data with the likelihood of the DCE data. When optimizing this joint distribution one may want to include one additional parameter acknowledging that the weights in both models may differ up to a monotonic transformation and that the variability may differ. This is done here by a single parameter relating both linear functions with each other and by assuming different variances for the heterogeneity (or errors) in the TTO data and the DCE data.

This approach 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. They add to the likelihood function by the density function f(t). Patients who have not yet died offer censored information. They add to the likelihood function by the cumulative density function (1-F(t)) or survival function S(t). The parameters of the survival model are found by multiplying the likelihood of people dying at the dates that have been observed and for those who did not, the likelihood that they are still alive at the date of their lost to follow up. 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.

Table 5.3 presents some results using the hybrid approach to the 5 parameter model. Table 5.4 shows them when considering the 20 parameter model.

Table 5.3 Comparison of DCE, TTO and Hybrid methods for the 5 parameter model

	DCE			TTO			Hybrid		
	estimate	95% CI		estimate	95% CI		estimate	95% CI	
Constant				1.185	(1.155 -	1.214)	1.178	(1.150 -	1.208)
MO	0.384	(0.352 -	0.416)	-0.063	-(0.070 -	-0.055)	-0.063	-(0.066 -	-0.059)
SC	0.204	(0.177 -	0.231)	-0.04	-(0.048 -	-0.033)	-0.034	-(0.038 -	-0.031)
UA	0.171	(0.142 -	0.201)	-0.035	-(0.043 -	-0.028)	-0.03	-(0.033 -	-0.026)
PD	0.464	(0.433 -	0.497)	-0.067	-(0.074 -	-0.060)	-0.073	-(0.077 -	-0.069)
AD	0.443	(0.411 -	0.475)	-0.067	-(0.075 -	-0.060)	-0.071	-(0.075 -	-0.067)

Table 5.4 Comparison of DCE, TTO and Hybrid methods for the 5 parameter model

	DCE			TTO			Hybrid		
	estimate	95% CI		estimate	95% CI		estimate	95% CI	
Constant				0.878	(0.844 -	0.913)	0.881	(0.856 -	0.905)
MO	0.476	(0.362 -	0.590)	-0.014	-(0.047 -	0.019)	-0.067	-(0.082 -	-0.051)
	0.555	(0.422 -	0.687)	-0.065	-(0.099 -	-0.030)	-0.084	-(0.101 -	-0.066)
	1.178	(1.047 -	1.310)	-0.213	-(0.251 -	-0.175)	-0.196	-(0.214 -	-0.178)
	1.613	(1.464 -	1.762)	-0.231	-(0.266 -	-0.197)	-0.255	-(0.272 -	-0.237)
SC	0.171	(0.048 -	0.294)	-0.035	-(0.067 -	-0.003)	-0.036	-(0.052 -	-0.020)
	0.289	(0.152 -	0.426)	-0.035	-(0.072 -	0.002)	-0.045	-(0.063 -	-0.027)
	0.722	(0.588 -	0.857)	-0.162	-(0.198 -	-0.126)	-0.129	-(0.147 -	-0.112)
	0.848	(0.719 -	0.977)	-0.173	-(0.206 -	-0.139)	-0.146	-(0.163 -	-0.130)
UA	0.213	(0.095 -	0.332)	-0.036	-(0.070 -	-0.002)	-0.035	-(0.051 -	-0.019)
	0.166	(0.036 -	0.297)	-0.071	-(0.107 -	-0.036)	-0.041	-(0.058 -	-0.024)
	0.560	(0.430 -	0.690)	-0.153	-(0.189 -	-0.117)	-0.108	-(0.125 -	-0.090)
	0.687	(0.554 -	0.820)	-0.120	-(0.153 -	-0.087)	-0.113	-(0.129 -	-0.096)
PD	0.376	(0.250 -	0.502)	-0.051	-(0.082 -	-0.020)	-0.059	-(0.075 -	-0.042)
	0.480	(0.350 -	0.610)	-0.096	-(0.133 -	-0.059)	-0.085	-(0.102 -	-0.067)
	1.213	(1.079 -	1.348)	-0.186	-(0.219 -	-0.154)	-0.196	-(0.213 -	-0.178)
	1.880	(1.734 -	2.026)	-0.280	-(0.315 -	-0.244)	-0.295	-(0.314 -	-0.276)
AD	0.361	(0.232 -	0.490)	-0.057	-(0.091 -	-0.023)	-0.057	-(0.074 -	-0.040)
	0.644	(0.511 -	0.776)	-0.099	-(0.137 -	-0.061)	-0.106	-(0.124 -	-0.088)
	1.315	(1.169 -	1.460)	-0.208	-(0.243 -	-0.173)	-0.212	-(0.231 -	-0.193)
	1.685	(1.537 -	1.833)	-0.260	-(0.294 -	-0.226)	-0.270	-(0.289 -	-0.252)

5.3 CORE ISSUE 2

Which model specification should be used to model the main effects: do we continue with dummy models or are there better alternatives?

One might say that the 20 parameter model – and in earlier days the 15 parameter model - is created to reflect the ordinal nature of the descriptors within each dimension. Now, these parameters are giving numeric values to concepts as slight, moderate severe and extreme. The current version of the EQ-5D is however using the same terminology in all dimensions, with the exception of the most extreme level where different terms are used in mobility, self care and usual activities than in pain and discomfort and anxiety and depression. This suggests that one might assume that the relative distance between those terms are similar for each dimension. Therefore, one might try to estimate a 9 parameter model and a 10 parameter model. The 9 parameter model has 5 parameters reflecting the weight given to each dimension and 4 to reflect the distance between the levels. The 10 parameter model has one more parameter to distinguish between the highest level in the first three dimensions (unable) versus the last two dimensions (extreme problems). Logically this can be done for the DC model, the TTO model and the hybrid model. Table 5.5 shows results for the DC models and Table 5.6 for the TTO models.

Table 5.5 9 and 10 parameter models for the DC data

	9 parameter model			10 parameter model		
	estimate	95% CI		estimate	95% CI	
slight	-0.854	-(1.804 -	-0.340)	0.741	(0.508 -	1.091)
moderate	-1.165	-(2.431 -	-0.472)	1.003	(0.705 -	1.467)
severe	-2.674	-(5.458 -	-1.085)	2.309	(1.667 -	3.296)
unable	-3.656	-(7.469 -	-1.491)	3.043	(2.182 -	4.315)
extreme				3.221	(2.318 -	4.609)
MO	-0.556	-(1.070 -	-0.211)	0.530	(0.361 -	0.730)
SC	-0.314	-(0.608 -	-0.115)	0.303	(0.206 -	0.423)
UA	-0.253	-(0.495 -	-0.092)	0.243	(0.163 -	0.345)
PD	-0.655	-(1.251 -	-0.249)	0.595	(0.405 -	0.813)
AD	-0.615	-(1.188 -	-0.232)	0.561	(0.383 -	0.766)

Table 5.6 9 and 10 parameter models for the TTO data

	9 parameter model			10 parameter model		
	estimate	95% CI		estimate	95% CI	
Constant	0.858	(0.828 -	0.888)	0.859	(0.826	0.892)
slight	-0.105	-(0.162 -	-0.056)	-0.049	-(0.075 -	-0.024)
moderate	-0.242	-(0.324 -	-0.175)	-0.108	-(0.144 -	-0.073)
severe	-0.601	-(0.769 -	-0.478)	-0.272	-(0.349 -	-0.194)
unable	-0.727	-(0.925 -	-0.579)	-0.296	-(0.382 -	-0.208)
extreme				-0.359	-(0.468 -	-0.259)

Table 5.6 9 and 10 parameter models for the TTO data (Continued)

	9 parameter model			10 parameter model		
	estimate	95% CI		estimate	95% CI	
MO	0.354	(0.017 -	0.450)	0.836	(0.623 -	1.164)
SC	0.249	(0.173 -	0.320)	0.601	(0.428 -	0.870)
UA	-0.049	(0.001 -	0.248)	0.460	(0.315 -	0.676)
PD	-0.108	(0.002 -	0.436)	0.730	(0.534 -	1.010)
AD	-0.272	(0.006 -	0.421)	0.700	(0.514 -	0.969)

5.4 CORE ISSUE 3

How should interaction be addressed? As diminishing misery (i.e. similar to the N3 term of the 3L models) or as "true" interactions?

It may be suggested that the inclusion of the N3 term in 3 level models was a reflection of existing interactions. The decrease in value due to adding a second or third 3 to one's health description was less than for the first 3. This may be seen as a reflection of diminishing disutility due to added misery or as some interaction. Classically interactions are created by multiplying dimensions, which was always a bit of a difficulty with the 20 parameter model. This however is much easier with the 9 and 10 parameter model where there the dimension structure is retained. First estimates are not reported here.

5.5 CORE ISSUE 4

The lowest possible value in the LT-TTO, when the lead time is exhausted, is -1. What is the impact of modeling lead time exhaustion as a censoring event thereby removing the floor effect?

When, in the current task, people suggest that they think that zero years in perfect health is to be preferred to 10 years in perfect health followed by 10 years in some miserable state, they have exhausted their lead time. So, they implicitly state that the value of that health state is equal or less than minus 1. In all former analyses we treated this value as being equal to minus 1. An alternative is to acknowledge that it is less or equal to minus one, just as in survival analysis when a person hasn't died but one wants to use the information that he has survived up till that date. This can be programmed in WinBugs and Table 5.7 presents some comparative results when using the 5 parameter model. The results indicate some remarkable differences. When taking account of censoring, the value for 11111 is 0.95 instead of 0.91, the value for 33333 is 0.30 instead of 0.36. The value for 44444 is negative 0.02 instead of positive 0.09 and the value for 55555 is estimated at -0.34 instead of -0.18.

Table 5.7 5 parameter model without and with the assumption that values of -1 are censored

	Without censoring			With censoring		
	estimate	95% CI		estimate	95% CI	
Constant	1.185	(1.155 -	1.213)	1.273	(1.241 -	1.273)
MO	-0.063	-(0.070 -	-0.055)	-0.075	-(0.083 -	-0.075)
SC	-0.040	-(0.048 -	-0.033)	-0.048	-(0.057 -	-0.048)
UA	-0.035	-(0.043 -	-0.028)	-0.043	-(0.051 -	-0.043)
PD	-0.067	-(0.075 -	-0.060)	-0.080	-(0.088 -	-0.080)
AD	-0.067	-(0.075 -	-0.060)	-0.078	-(0.086 -	-0.078)

5.6 SECONDARY ISSUE 1

Since not all respondents use the same heuristics when valuing health states, can we identify groups of respondents who use the same heuristics and model them separately?

When data from all respondents are pooled and jointly modeled one obtains a model for the whole sample, averaging out individual differences between respondents. Implicitly this means that it is assumed that all respondents use the same heuristics. However, it is likely that respondents differ in their heuristics. This is most obvious for the severe health states. As can be seen in the histograms and charts presented in Appendix 5A, some respondents regard all states as better than dead, while other respondents value the worst states at 0, while still others value the worst states at -1. Furthermore, the weights given to each dimension differs between respondents. This means that different respondents use different heuristics and different scales.

In order to get some insight into the difference between respondent groups we divided the 986 respondents over 5 groups. Group 1 includes the non traders (i.e. respondents that gave the value 1 to all states). Group 2 includes the respondents that give a value larger than 0 for all health states (i.e. respondents that use the scale from [1,0>). Group 3 includes the respondents that give a value larger than or equal to 0 for all health states (i.e. respondents that use the scale from [1,0]). Group 4 includes the respondents that give a value larger than -1 for all health states (i.e. respondents that use the scale from [1,-1>]). Group 5 includes the respondents that give a value larger than or equal to -1 for all health states (i.e. respondents that use the entire scale from [1,-1]). The 5 parameter and the 20 parameter models were fitted separately for each group. The results can be found in Tables 5.8 and 5.9.

Table 5.8 5 parameter model fitted on the 5 different subsets of the data

	All (N=986)	Group 1 (N=10)	Group 2 (N=205)	Group 3 (N=327)	Group 4 (N=266)	Group 5 (N=178)
Constant	1.184	1	1.060	1.114	1.305	1.269
MO	-0.063	.	-0.028	-0.048	-0.076	-0.115
SC	-0.040	.	-0.016	-0.037	-0.045	-0.067
UA	-0.035	.	-0.021	-0.032	-0.042	-0.045
PD	-0.067	.	-0.033	-0.052	-0.094	-0.098
AD	-0.067	.	-0.033	-0.052	-0.086	-0.111
Adj R^2	0.267	.	0.272	0.391	0.381	0.382

Table 5.9 20 parameter model fitted on the 5 different subsets of the data

	All (N=986)	Group 1 (N=10)	Group 2 (N=205)	Group 3 (N=327)	Group 4 (N=266)	Group 5 (N=178)
Constant	-0.122	0	-0.096	-0.125	-0.096	-0.196
MO2	-0.014*	.	-0.011*	-0.039	-0.028*	0.003*
MO3	-0.065	.	-0.057	-0.043	-0.058	-0.200
MO4	-0.213	.	-0.096	-0.160	-0.234	-0.382
MO5	-0.231	.	-0.100	-0.202	-0.292	-0.398
SC2	-0.035	.	-0.005*	-0.027*	-0.037*	-0.065*
SC3	-0.035	.	-0.023*	-0.037*	-0.034*	-0.052*
SC4	-0.162	.	-0.073	-0.131	-0.179	-0.190
SC5	-0.173	.	-0.065	-0.152	-0.198	-0.313
UA2	-0.036	.	-0.018*	-0.029*	-0.033*	-0.081*
UA3	-0.071	.	0.013*	-0.056	-0.077	-0.125
UA4	-0.153	.	-0.080	-0.126	-0.176	-0.230
UA5	-0.120	.	-0.081	-0.109	-0.135	-0.152
PD2	-0.051	.	-0.016*	-0.045	-0.066	-0.049*
PD3	-0.096	.	-0.073	-0.048	-0.099	-0.214
PD4	-0.186	.	-0.106	-0.166	-0.241	-0.273
PD5	-0.280	.	-0.121	-0.196	-0.380	-0.441
AD2	-0.057	.	-0.011*	-0.042	-0.074	-0.125
AD3	-0.099	.	-0.043	-0.119	-0.129	-0.134
AD4	-0.208	.	-0.090	-0.178	-0.249	-0.385
AD5	-0.260	.	-0.120	-0.205	-0.343	-0.413
Adj R^2	0.271	.	0.275	0.397	0.386	0.386

*Not significant at the 95% level

As can be seen in this table there is quite a bit of difference in the parameter estimates obtained for each group. As expected, the size of the parameter estimates differ indicating different levels of how good or bad a health states is valued. However, the relative importance of the different dimensions also differs between groups. For example, in groups 2 and 3 PD and AD are valued equally, while in group 4 PD is valued lower than AD, and in Group 5 AD is valued lower than PD. Dividing the sample in these 5 groups, removes some of the heterogeneity observed in the TTO data, as indicated by the higher values of adjusted R2 for each group compared to the adjusted R^2 for the full data set.

The results from the 20 parameter model are in line with those from the 5 parameter model, in the sense that there are quite substantial differences between the groups and that the model fit is better for the models based on each group separately than the fit on the complete data set. Furthermore, it can be seen that the reversed order of UA4 and UA5 in the model on the full data set is present in all of the subgroups as well (except the non-traders).

5.7 SECONDARY ISSUE 2

Should we use random coefficient models on EQ-VT data?

The fact that people answer differently, may be a reflection of many different processes. The two main are that there is random errors and that people have different opinions. In case of the latter, these differences may concern the position of dead, the relative value of the different dimensions, the minimal severity before one starts to trade etc. One way to model this is for example a random effects model. This however, may not be that appropriate here as this assumes that there is variability in the intercept which may not be that logical, given that most individuals are supposed to start at an intercept of 1. As an alternative, the results are presented of two approaches. The first assumes that there is a model $y = \alpha + \beta_x$ where β_x is multiplied with a parameter h which follows a normal distribution with mean 1 and variance σ^2. Table 5.10 presents results using the Spanish data.

The results imply a certain variability around for example the value of 55555. While the mean value is estimated at -0.22076 one may estimate a distribution with 95% ranging between -1.61and + 1.17. The latter suggest a value which is way too high, forcing us to think again about whether linear regression is the most appropriate approach.

Table 5.10 Random coefficient model

	estimate	95% CI	
Constant	1.203	(1.174 -	1.231)
MO	-0.063	-(0.072 -	-0.055)
SC	-0.043	-(0.051 -	-0.034)
UA	-0.040	-(0.048 -	-0.032)
PD	-0.068	-(0.077 -	-0.059)
AD	-0.073	-(0.082 -	-0.065)
h mean	0.994	(0.922 -	1.067)
h σ	4.057	(3.367 -	4.908)

The second assumes that the parameter h has a discrete distribution with positive point mass at 3 points with parameters h1, h1-h2 and h1- h2 - h3. This is as if there are three models and that people belong to either one of these three models. Table 5.11 presents the results using the Spanish data.

Table 5.11 Random coefficient model

	estimate	95% CI	
Constant	1.193	(1.169 -	1.217)
MO	-0.115	-(0.133 -	-0.097)
SC	-0.093	-(0.109 -	-0.077)
UA	-0.139	-(0.160 -	-0.118)
PD	-0.168	-(0.189 -	-0.148)
AD	-0.145	-(0.161 -	-0.128)
h1	0.988	(0.915 -	1.072)
h2	0.604	(0.558 -	0.654)
h3	0.303	(0.279 -	0.329)
P(h1)	0.087	(0.078 -	0.095)
P(h2)	0.210	(0.194 -	0.229)
P(h3)	0.703	(0.684 -	0.721)

Within this approach – with vague priors- one estimates there to be three groups. When considering the value of 55555 it is estimated that 8.7% gives it the value -2.06, 21.0% gives it the value -0.7 and 70.3% gives it the value 0.925. These results suggest that this approach needs some more work.

5.8 SECONDARY ISSUE 3

Should we use the mean or the median as a measure of central tendency in composite TTO data?

The choice between means and medians is an issue that is outside the scope of this paper. However, it does make one think about the estimation techniques. Figure 5.6 presents a comparison of the means and medians when using the Spanish TTO data. One finds that there are a number of health states with the same medians, most notably at 0.5, zero and 0.95. This first makes us realize once more that we do not really have continuous data. It also makes us realize that when considering TTO data there is a choice between using means and medians. No such choice seems to exist when using the DC data. The DC models as used here start with the assumption of a symmetric error distribution for both utilities and derive a symmetric error distribution for the difference between those. Now, the difference between asymmetric distributions may still be symmetric but this may only be in exceptional cases. This observation shows that further work may be needed before being able to link the data from TTO and DCE and or to use a hybrid approach where the assumption of the normality of the "error distribution" is used (as in all DC models), which is obviously false.

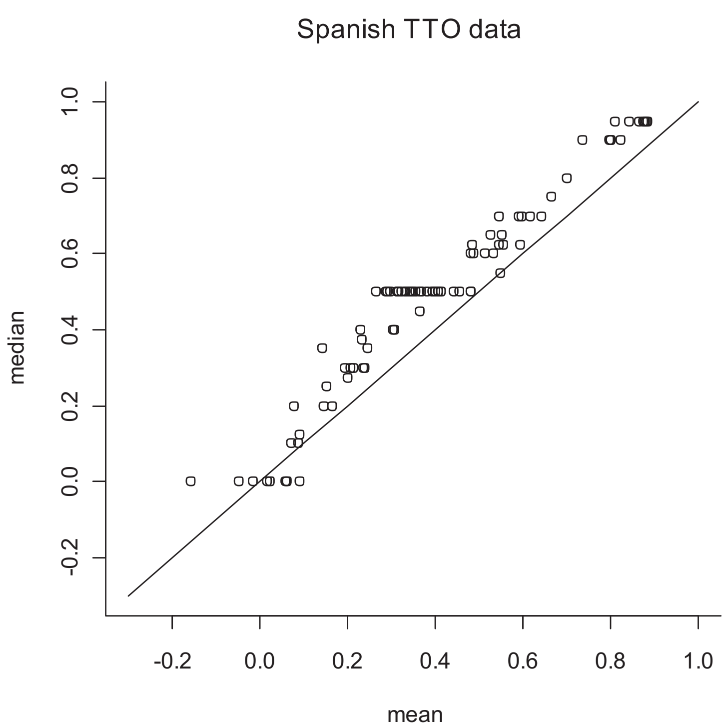

Figure 5.6 Mean versus median of the observed TTO data

5.9 SECONDARY ISSUE 4

How does the precision of the answers relate to the speed of iteration required to obtain those answers?

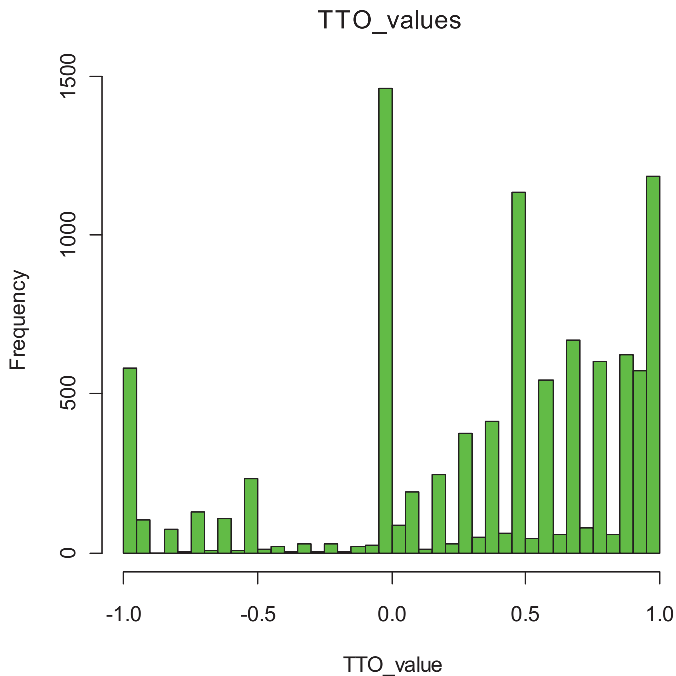

Figure 5.7 distribution of answers

Figure 5.7 presents the distribution of answers and one may observe that many of the answers are concentrated on the rounded figures.

From the data about how many iterations people use, one may learn that many of those numbers are already found during the first iterations, and as such one might suggest that individuals are confronted with a trade-off between precision and speed or convenience. If such trade-off is made, it seems logical to put some salt on the fast responses and to take responses which are obtained after some iterations more seriously. This can be done by not using the real values as answers to the TTO questions but ranges. Rather loosely, the following thoughts are put forward.

During the first iteration 254 health states are set at the value 1. This is set as between 0.8 and 1. During the second iteration, 998 are set at 0 and 2 at 0.95. This is interpreted as being between 0±0.125 at between 0.95±0.0125. During the third iteration 342 are set at 0, 969 at 0.5, 5 at 0.9 and 3at 1. This is interpreted as being 0±0.1, 0.5±0.1, 0.9±0.0125 and as between 0.9875 and 1. During the fourth iteration 195 are set at -0.5, 19 at 0.05,327 at 0.4 and 448 at 0.6. This is interpreted as being -0.5±0.125, 0.05±0.0125, 0.4±0.05 and 0.6±0.05. Arbitrary, all estimates after iteration 4 are given a margin of uncertainty of 0.025. Table 5.12 presents comparative results with and without the added uncertainty using a 5 parameter mode on the Spanish data. Surprisingly, there are absolutely no differences.

Table 5.12 comparative results with and without added uncertainty

	No added uncertainty			Added uncertainty		
	estimate	95% CI		estimate	95% CI	
Constant	1.185	(1.155 -	1.214)	1.179	(1.150 -	1.209)
MO	-0.063	-(0.070 -	-0.055)	-0.063	-(0.070 -	-0.055)
SC	-0.040	-(0.048 -	-0.033)	-0.040	-(0.047 -	-0.032)
UA	-0.035	-(0.043 -	-0.028)	-0.035	-(0.043 -	-0.028)
PD	-0.067	-(0.074 -	-0.060)	-0.067	-(0.074 -	-0.059)
AD	-0.067	-(0.075 -	-0.060)	-0.067	-(0.075 -	-0.059)

CONCLUSIONS AND DISCUSSION

Five level EQ-5D valuation studies can be carried out in numerous ways and so also numerous approaches can be followed to derive value functions. In this paper we address a selected number of issues which one may meet in every valuation study and some that are typical for the type of studies which have been promoted within the EQ-5D valuation task force. This implies a computer assisted interview combining discrete choices with time trade off questions. This paper tries to present a number of ideas and thoughts about the modelling when the data becomes available. The availability of the data from the Spanish evaluation study has been instrumental in doing so.

Every study may best start with an overview of what the data looks like. The Dutch saying "tekenen voordat je gaat rekenen" or "draw before one starts to calculate" is a useful motto. Using the Spanish data we find that the design seemed to do what was expected. Nothing alarming was found, the DCE data were nicely spread except for a few comparisons, the TTO data showed a type of clustering behaviour suggesting a relatively crude type of behaviour rounding towards central numbers (i.e. digit preference). A substantial number of people did not want to trade time for the better health states and the valuation of the worst health state varied from +1 to -1 with peaks on -1, -0.5 and 0.5.

As a first step towards modelling one may start with the "standard" models. Probit or Logit analysis for the DC-questions and linear regression for the TTO-questions. Within these one may use different specifications and here we illustrated the use of 5, 9, 10 and 20 parameter models for both types of data. The 10 parameter model might make most sense from a theoretical point of view. Here - with the Spanish data - it also appears to fit the data very well.

A second step may be to investigate alternative forms to the linear form without interactions. The inclusion of N2, N3, N4 and N5 terms springs to mind. Modeling interactions by the inclusion of products of each dimension is rather complicated when considering dummy models (20 parameter model). Now, with model-specifications that hold the dimension structure one might take this route again. This has not been pursued yet here. A third step may be to reconsider the underlying assumptions of the linear regression models and the Logit models.

Another issue, with respect to the linear regression models, is that the explanatory variable is truncated at 1 and that this may have implications to the error distribution. A transformation, such as a logistic model, could be used to correct for this. The results of such an exercise are operational but not reported here.

Before taking the second step one may want to decide about how to interpret the data of health states which are scored at minus one. In essence, respondents indicate that the value is at or below minus 1 and do not give information about how much. The approach that has been investigated here is to treat the data as censored observations. This seems theoretically elegant but leaves us with a few obstacles. First, when interpreting the data like this one may doubt the validity of the mean TTO values since they use "minus ones" for the censored values and as such may overestimate the real mean values, which would have been observed when the data weren't censored. Second, it assumes a linear extrapolation into the negative area and when people "really, really, really" don't want to be in a heath state, some exponential model may be more appropriate. the differences may be substantial as more health states may end up in the negative spectrum as was indicated by the results on the Spanish data. Further research may be needed. From a theoretical point of view, one should take censoring into account.

DCE data come with advantages and disadvantages, as do TTO data. TTO data may often tell you that 21111 has the same value of 11111. DCE data will not. DCE data only give relative orderings while TTO data present real values (albeit with limited precision). Here, many considerations are set aside and it is assume that both types of data are generated by some common notion about the disutility of a health state. A likelihood approach is used to combine both sets of data leading to some type of middle ground between the TTO model and the DCE model. In this case, the results worked out beautifully in the sense that while both the DCE and the TTO models indicate inconsistent parameter values, the hybrid model does not. This however may well be coincidental. Experience with the multi-country study showed that the hybrid approach most often nests itself between the results of the DCE and TTO, as one might expect.

When addressing the ideas about means and medians one may once more reconsider the underlying assumptions of the DCE model. It derives its parameters from the assumption of normally distributed errors while the data is generated more by differences of opinion than by random errors. Here, using the Spanish data, we find that the DCE models lead to similar estimates as the TTO models and as such there doesn't seem to any objection to pool them. The question is what one would do if this is not the case. Is this a matter of belief? TTO, Hybrid or DCE? Hybrid only when DCE and TTO agree? Another issue addressed in this paper concerns the heterogeneity of the population. Some respondents think each health state is above zero. Some think no life years should ever be traded. Some seem to think that this should only be done in case of some level of severity. This may all be irrelevant while searching for one average value function, however, it may be relevant for a better understanding of the data and as such of a better model describing the data and as such for better interpolations. The Spanish data once more confirms that there are different groups and some first steps are taken to modelling the different groups. First, by taking them apart, second, by testing some random coefficient models. A variety of alternatives are possible.

One alternative, not pursued yet is to use beta-regression. When eye-balling the data per state one might see that the distribution moves as when changing the parameters of a beta distribution, skewed to the right for the healthy states, skewed to the left for the severe states. Is it possible to link the severity of the state to the parameters describing the distribution? It may be worthwhile to consider this path of analysis.

The data from the multi country study as well as the data from the Spanish study have triggered many ideas about how to model the data. This paper addresses a number of them, primarily for discussion. The next weeks and months will proof to be exiting as more data will become available and more people will start to play with them. An exciting period is about to begin.

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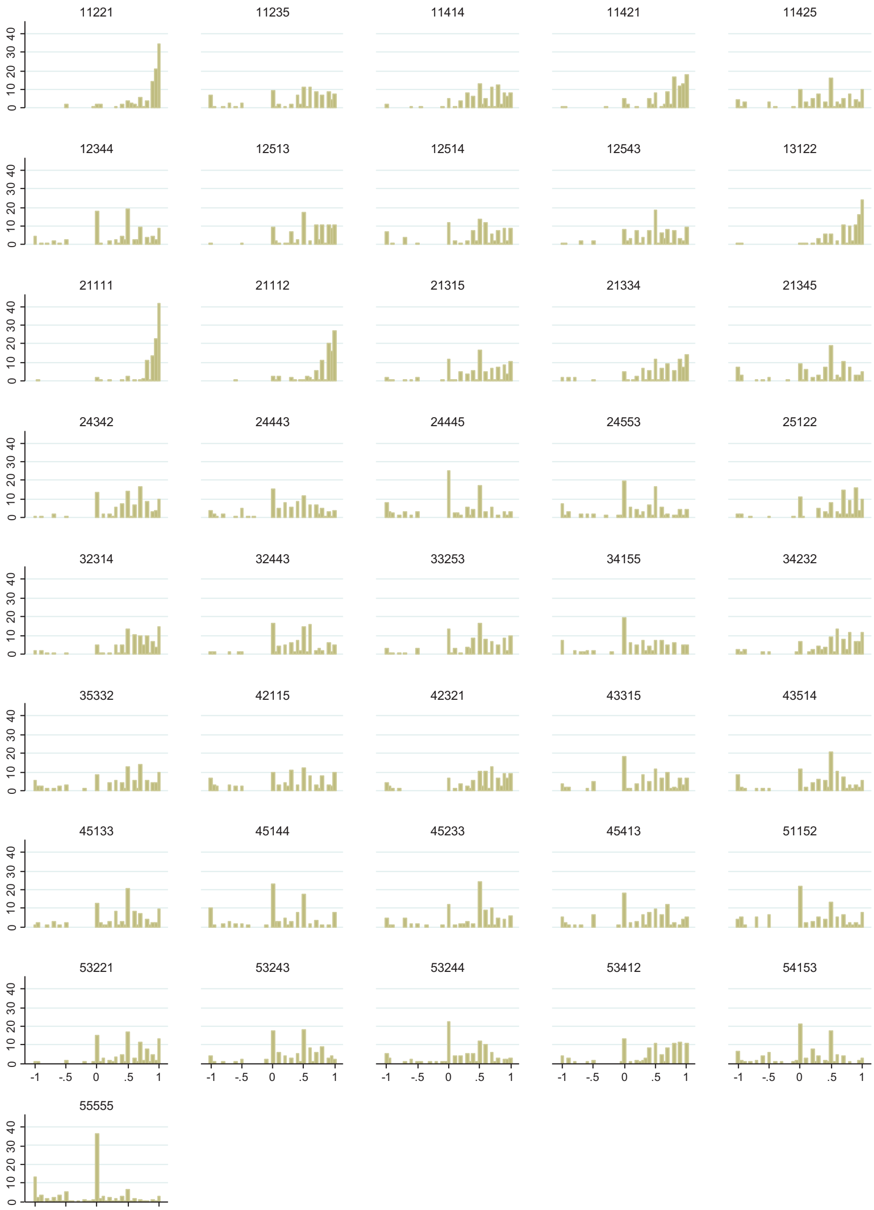
APPENDIX 5A
DETAILS OF THE TTO DATA

Number of observations and mean utility value for the 86 TTO states

EQ state	N	mean Utility	EQ state	N	mean Utility
11112	207	0.874	31524	103	0.405
11121	203	0.881	31525	100	0.317
11122	88	0.800	32314	104	0.550
11211	188	0.879	32443	96	0.393
11212	96	0.821	33253	104	0.398
11221	104	0.810	34155	96	0.211
11235	104	0.368	34232	88	0.511
11414	98	0.556	34244	96	0.263
11421	100	0.699	34515	104	0.230
11425	92	0.349	35143	98	0.380
12111	192	0.842	35245	104	0.076
12112	96	0.800	35311	88	0.481
12121	96	0.864	35332	92	0.330
12244	100	0.311	42115	92	0.246
12334	104	0.597	42321	88	0.486
12344	105	0.343	43315	103	0.305
12513	105	0.591	43514	96	0.288
12514	104	0.391	43542	96	0.303
12543	96	0.441	43555	88	-0.049
13122	92	0.736	44125	105	0.163
13224	88	0.485	44345	105	0.056
13313	100	0.664	44553	96	0.016
14113	103	0.641	45133	96	0.365
14554	105	0.088	45144	104	0.088
15151	103	0.333	45233	100	0.291
21111	196	0.883	45413	92	0.230
21112	105	0.796	51152	92	0.151
21315	103	0.455	51451	104	0.191
21334	104	0.546	52215	96	0.365
21345	96	0.297	52335	88	0.235
21444	98	0.340	52431	103	0.343
22434	92	0.355	52455	100	-0.019
23152	96	0.406	53221	105	0.480
23242	104	0.592	53243	98	0.322
23514	96	0.549	53244	98	0.206
24342	104	0.480	53412	104	0.413
24443	103	0.237	54153	103	0.071
24445	88	0.088	54231	104	0.313
24553	92	0.145	54342	105	0.059
25122	100	0.546	55225	104	0.200
25222	98	0.614	55233	100	0.143
25331	98	0.527	55424	96	0.022
31514	98	0.531	55555	986	-0.158

Histograms for the 86 TTO states


11221
11235
11414
11421
11425
12344
12513
12514
12543
13122
21111
21112
21315
21334
21345
24342
24443
24445
24553
25122
32314
32443
33253
34155
34232
35332
42115
42321
43315
43514
45133
45144
45233
45413
51152
53221
53243
53244
53412
54153
55555
0 10 20 30 40
-1 -.5 0 .5 1

The value of health states versus the number of moves made by respondents, This is based on all data from the 86 TTO states.

																				UTILITY
MOVES	-1	-0,95	-0,9	-0,8	-0,75	-0,7	-0,65	-0,6	-0,55	-0,5	-0,45	-0,4	-0,35	-0,3	-0,25	-0,2	-0,15	-0,1	-0,05	0
1																				
2																				998
3																				342
4										194										
5								95			7									6
6						121			3	12		11								
7				64			2	3		11	2			17						1
8			100		2	2		4	4	1		4	1			19				
9		116		2			3	1		4	1	1		5	1			11		30
10	438		2			1			1			1				1	2		17	5
11		7		2		1	1	2		1		1		2		2		4		42
12	4							1		1				1						4
13		1		1				1						1		1		2		8
14	1			2						1						1			2	5
15			1							1		1								8
16	2	1				2				2								1	1	1
17	5											2				2	1		1	1
18		1		1										1		1				
19							1			1										
20	1							1										1		1
21																1				1
22	1																			2
23						1														
24																				
25																				
26			1																	2
27																			1	
28																				
29																				
30																				1
32	1																			
33										1										
34	1																			
35	1																			1
36																				
37										1										
39																				1
46										1										
49																				
57																				
63						1														
85																				
88																				
95						1														
TOTAL	455	126	104	72	2	130	7	108	8	232	10	21	1	27	1	28	3	19	22	1460

showing the iterative paths taken by the respondents to come to their TTO answer.

UTILITY																				
0,05	0,1	0,15	0,2	0,25	0,3	0,35	0,4	0,45	0,5	0,55	0,6	0,65	0,7	0,75	0,8	0,85	0,9	0,95	1	TOTAL
																			254	254
																		4		1002
									969								5		3	1319
19							327				448									988
	2				327			41		34			590				2			1104
3			206			35	5		91		16	49			533					1085
	150			24	9		41	10		1	46		20	53		1	523			978
49	1	10	5		23	7	6	1	31	4	2	4	22		10	46		426		784
	17		24	2		1	13	2	19	1	9		2	11	24		51		890	1241
5	8	1	3	2	9	2	6	4	11	1	9	3	9	1	6	5	5	107		665
2	3	1	3		1		6	1	2		2		7	6	1	1	23	3	17	144
3	5		2		4	1	2		5	1	1		1	3	8		2	11	1	61
			1				1	1			2		3	1	4	2	5		3	38
1	2				1		1				2		5		4		1	8		37
1	1					1			1		3				1			3	6	28
	1						3								2	1	1	7	2	27
1	1								3				1				1	2		21
							1		2	1	2		1						1	12
										1	1		2		1					7
	1												1				1		1	8
											1	1			1					5
															3			1	1	8
1							1						1				3	1	4	12
													1		1					2
			1																	1
																		1		4
														1						2
											1		1							2
														1					1	2
	1																			2
								1												2
																				1
																				1
																				2
1																			1	2
																				1
																				1
																				1
							1													1
			1																	1
																				1
															1					1
					1															1
																				1
86	193	12	246	28	375	47	414	61	1134	44	545	57	667	77	600	56	623	574	1185	9860

The value of health states versus the number of moves made by respondents, show-
This chart is based only on data from the 11 very mild TTO states with only one or

MOVES	-1	-0,95	-0,7	-0,6	-0,5	-0,05	0	0,05	0,1	0,2	0,3	0,35	0,4
1													
2							23						
3							6						
4					4			4					7
5				1							17		
6					3			1		3		2	
7							1		3		2		1
8				1				3	1				
9		1											1
10	3							1			1		1
11							1						2
12													
13													
14						1	1						
15									1			1	
16									1				
17													
18													
20													
21													
22													
23								1					
26													
85													
95			1										
TOTAL	3	1	1	2	7	1	32	10	6	3	20	3	12

ing the iterative paths taken by the respondents to come to their TTO answer.
two dimensions at level 2 while the rest are at level 1.

0,45	0,5	0,55	0,6	0,65	0,7	0,75	0,8	0,85	0,9	0,95	1	TOTAL
											107	107
										2		25
	35								1		2	44
			27									42
3		7			63							91
	4		2	7			111					133
			2		1	10		1	187			208
	3	2			1		2	16		227		256
	2		1			5	5		21		464	500
1					3	1		2	2	65		80
						1	1		8	3	8	24
			1			2	2		1	9		15
1					1		1	1	2		3	9
					1		1			3		7
										2	2	6
									1	4	2	8
									1	1		2
		1									1	2
											1	1
			1	1			1					3
										1		1
										1	2	4
										1		1
							1					1
												1
5	44	10	34	8	70	19	125	20	224	319	592	1571

The value of health states versus the number of moves made by respondents, show-
This chart is based only on data from state 55555.

MOVES	-1	-0,95	-0,9	-0,8	-0,75	-0,7	-0,65	-0,6	-0,55	-0,5	-0,45	-0,4	-0,3	-0,2	-0,15	-0,1	-0,05	0
1																		
2																		262
3																		66
4										41								
5								28			2							
6						21			2	2		6						
7				17						2	1		5					
8			35		2	1		2	1	1		1		10				
9		23		1				1		2			1			5		4
10	124		1						1						1		7	2
11		1				1												15
12								1		1								1
13								1										1
14				1						1				1				2
15			1															4
16	2									1								
17	1														1		1	
19							1											
20								1								1		1
22																		
23																		
26																		1
32	1																	
36																		
37										1								
39																		1
Total	128	24	37	19	2	23	1	34	4	52	3	7	6	11	2	6	8	360

ing the iterative paths taken by the respondents to come to their TTO answer.

0,05	0,1	0,15	0,2	0,25	0,3	0,35	0,4	0,45	0,5	0,55	0,6	0,7	0,75	0,8	0,9	0,95	1	Total
																	13	13
																		262
									55									121
4							19				14							78
					13			1		2		8						54
1			22			1	1		5					4				65
	16			3			3				1		1		7			56
9		1					1		3							3		70
	7			1					2		1						12	60
	5		2				1									1		145
	1										1	1						20
						1												4
							1					1			1			5
1							1											7
									1									6
																		3
									1			1						5
																		1
																		3
														1				1
																	1	1
																		1
								1										2
1																		1
																		1
																		1
16	29	1	24	4	13	2	27	2	67	2	17	11	1	5	8	4	26	986

APPENDIX 5B

Pair	state A	state B	N	%A	%B	Pair	state A	state B	N	%A	%B
1	35231	53554	29	100%	0%	51	21423	13114	24	42%	58%
2	43534	32125	35	29%	71%	52	51331	22421	24	17%	83%
3	44115	21455	49	65%	35%	53	34345	51325	40	43%	58%
4	13111	11215	29	93%	7%	54	23442	25414	34	68%	32%
5	33223	21232	31	6%	94%	55	42122	31325	40	65%	35%
6	15244	44241	38	32%	68%	56	12151	35543	29	86%	14%
7	12145	15344	31	48%	52%	57	52523	54142	33	61%	39%
8	32442	54441	41	95%	5%	58	51114	41253	38	68%	32%
9	44521	41153	32	69%	31%	59	25235	13413	38	13%	87%
10	11214	45312	30	70%	30%	60	42243	35433	48	48%	52%
11	35211	42551	45	89%	11%	61	52544	34222	34	15%	85%
12	24155	32534	35	17%	83%	62	11545	14113	41	12%	88%
13	22341	45145	31	97%	3%	63	23451	34354	33	97%	3%
14	33432	15551	35	71%	29%	64	43141	25554	31	87%	13%
15	13251	53313	29	45%	55%	65	52211	11325	34	62%	38%
16	35554	55211	31	16%	84%	66	24314	43222	36	42%	58%
17	42323	55223	36	89%	11%	67	31451	45431	49	47%	53%
18	14533	21542	39	69%	31%	68	42255	55524	30	40%	60%
19	13432	13245	36	81%	19%	69	31135	11444	31	61%	39%
20	42421	54255	29	100%	0%	70	34355	43342	33	18%	82%
21	52132	21534	30	63%	37%	71	45531	14334	40	53%	48%
22	41325	13445	36	69%	31%	72	51354	41335	36	31%	69%
23	54455	55234	32	9%	91%	73	43244	25522	36	22%	78%
24	33424	41542	31	68%	32%	74	14455	15514	31	16%	84%
25	25342	51152	30	83%	17%	75	53431	52255	39	87%	13%
26	23551	43135	43	47%	53%	76	51522	45244	39	85%	15%
27	34132	24445	45	96%	4%	77	11352	31413	43	30%	70%
28	23443	25113	49	12%	88%	78	22413	22331	38	29%	71%
29	44134	22352	48	13%	88%	79	23235	11141	30	17%	83%
30	51255	31343	43	9%	91%	80	14333	24424	33	88%	12%
31	51311	32154	33	91%	9%	81	35521	43355	31	84%	16%
32	44151	53242	38	37%	63%	82	12253	12551	36	50%	50%
33	34333	33142	36	47%	53%	83	44234	33441	29	28%	72%
34	14122	54231	35	94%	6%	84	43245	34324	29	0%	100%
35	55335	53442	29	31%	69%	85	44351	24415	36	22%	78%
36	11512	22241	40	73%	28%	86	52223	54132	41	59%	41%
37	14552	55325	38	63%	37%	87	11234	21532	41	59%	41%
38	54423	32314	29	14%	86%	88	44323	21525	31	45%	55%
39	34442	15214	30	27%	73%	89	41545	33531	31	10%	90%
40	45542	42133	29	3%	97%	90	24145	32253	36	42%	58%
41	31331	35124	30	83%	17%	91	22433	12443	35	77%	23%
42	23134	14314	39	38%	62%	92	33224	42113	34	35%	65%
43	25312	41532	36	89%	11%	93	33243	11115	35	20%	80%
44	32334	22254	31	81%	19%	94	22512	55313	48	92%	8%
45	31521	43152	31	97%	3%	95	25515	22251	31	45%	55%
46	35321	53215	24	83%	17%	96	53551	21224	33	18%	82%
47	24453	41331	24	13%	88%	97	45552	32413	49	4%	96%
48	41315	15121	36	17%	83%	98	34412	54253	30	90%	10%
49	51324	34543	35	54%	46%	99	23233	12411	29	21%	79%
50	44123	51232	31	45%	55%	100	25545	35225	31	6%	94%

DESCRIPTION OF THE DC DATA

Pair	state A	state B	N	%A	%B	Pair	state A	state B	N	%A	%B
101	53125	31415	33	33%	67%	151	13131	23113	41	71%	29%
102	15534	43454	48	83%	17%	152	52155	45231	31	6%	94%
103	35235	42325	24	38%	63%	153	22123	11155	29	79%	21%
104	15113	14434	33	88%	12%	154	51552	35513	38	8%	92%
105	24523	45125	45	84%	16%	155	23531	53133	35	86%	14%
106	34234	13533	35	14%	86%	156	41114	24142	49	51%	49%
107	51123	43451	34	74%	26%	157	22222	25514	35	94%	6%
108	55235	22533	31	3%	97%	158	12521	41115	48	79%	21%
109	15241	12352	34	65%	35%	159	21445	55141	29	45%	55%
110	25145	52244	38	63%	37%	160	15335	43532	36	42%	58%
111	15424	33322	31	13%	87%	161	41312	24253	29	93%	7%
112	35322	41535	41	83%	17%	162	42452	23144	38	21%	79%
113	52111	11431	45	36%	64%	163	15555	53455	32	75%	25%
114	25212	32443	43	81%	19%	164	22343	34513	32	34%	66%
115	22453	13442	33	9%	91%	165	53422	42525	38	74%	26%
116	14344	52454	34	88%	12%	166	33443	54133	31	39%	61%
117	45533	14444	38	42%	58%	167	35431	51323	36	56%	44%
118	21522	25324	29	76%	24%	168	54424	15321	43	9%	91%
119	55153	22521	48	13%	88%	169	11445	32115	45	27%	73%
120	42441	21415	31	35%	65%	170	33225	53314	31	52%	48%
121	21114	52432	30	73%	27%	171	22544	35452	24	75%	25%
122	21354	41321	45	13%	87%	172	55534	33355	41	39%	61%
123	52422	55254	35	91%	9%	173	54121	44322	36	56%	44%
124	35252	32254	30	57%	43%	174	15351	14312	40	23%	78%
125	21235	12243	48	42%	58%	175	42153	53151	29	55%	45%
126	41424	35533	38	47%	53%	176	13222	31131	36	39%	61%
127	14224	32322	39	23%	77%	177	23122	12415	38	74%	26%
128	45515	34433	29	10%	90%	178	54454	24511	29	7%	93%
129	23231	25323	36	86%	14%	179	53543	41215	35	29%	71%
130	13334	45441	33	73%	27%	180	44145	45432	39	28%	72%
131	23513	52254	36	97%	3%	181	13553	31234	30	33%	67%
132	43412	13342	43	44%	56%	182	51131	35353	24	92%	8%
133	51424	35525	36	69%	31%	183	21335	44551	40	65%	35%
134	25332	51544	49	92%	8%	184	54344	15411	30	7%	93%
135	54555	35535	45	9%	91%	185	34134	45325	43	81%	19%
136	41552	22422	33	9%	91%	186	41431	24212	31	29%	71%
137	23552	32244	36	31%	69%	187	21111	12121	38	50%	50%
138	42512	23544	30	93%	7%	188	12111	21121	35	74%	26%
139	13515	11324	29	14%	86%	189	11211	22111	31	77%	23%
140	32241	51525	31	81%	19%	190	11121	21211	29	86%	14%
141	33111	32545	31	100%	0%	191	11112	12221	32	75%	25%
142	44231	25533	32	66%	34%	192	11122	23111	33	52%	48%
143	22411	43133	31	77%	23%	193	11212	22112	49	86%	14%
144	51214	45153	40	58%	43%	194	12112	22211	33	55%	45%
145	43525	23444	29	31%	69%	195	21112	12211	32	28%	72%
146	32211	14211	31	65%	35%	196	11221	22122	39	95%	5%
147	31444	11353	36	50%	50%						
148	55244	53531	35	3%	97%						
149	35312	14422	30	53%	47%						
150	45115	54225	33	82%	18%						