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The optimal hybrid: Experimental design and modeling of a combination of TTO and DCE

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3.1 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. This increase in number of health states might prove to hamper the feasibility of valuation studies when using TTO as an elicitation technique. Therefore 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 Modelling (DCM). DCM has already been used successfully in fields such as transport economics and marketing. Also the models used in DCM are Random Utility Models and therefore fit into the random utility framework. Because of the potential benefits of DCM the EuroQol Group's Valuation Taskforce is exploring the use of DCE as a technique to elicit EQ-5D value sets in addition to the existing techniques TTO and VAS.

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 (DCE-derived) values for EQ-5D health states in order to investigate whether or not modeling DCE 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. The main difficulty in applying DC models was that these models generated values on an arbitrary scale, not on the metric of the quality (of life) component of the QALY scale. This means that DCE-based values need to be anchored on the utility scale. In the 3L pilot 2 anchoring strategies were tested. The first was the use of the observed TTO value for EQ-5D state 33333 and the set value of 1 for EQ-5D state 11111 as anchors points. The second was anchoring the values derived from DCE data on the QALY scale directly by using ‘dead’ as a choice option. In both cases the DC models produced higher values than TTO.

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Overall, it was found that a strategy based on TTO data supplemented by health-state values derived from DC modeling might be a feasible and accurate option. Although differences in results from the two conceptually different valuation methods were found, there seemed to be a clear systematic relation that would make conversion from one method to the other feasible and defendable. However, if combined use of DC modeling and TTO is considered for health-state valuation, the strategy for linking DC and TTO data needs to be further explored. The use of a larger number of observed TTO values allows for more refined ways of adjusting the parameters of the DC model to fit the TTO dataset that might improve the comparability of TTO and DC values. This might also circumvent the problem that the value difference between the best EQ-5D state (11111) and the other states cannot be reliably estimated in the DC model. Perfect health will always be chosen over other health states, which results in an infinite value difference. Using '11111' as the anchor point may therefore have contributed to systematic differences between TTO- and DCE-derived values.

After the successful completion of the Dutch DCE pilot project on the EQ-5D-3L, the valuation task force decided to further investigate the combination of DCE and lead time TTO data for the estimation of value sets for the EQ-5D-5L. For this purpose a multinational pilot study for the valuation of EQ-5D-5L has been developed that will include both DCE and LT-TTO tasks (i.e. the four country (4C) study). For the development of the study protocol two of the more "technical" issues that needed to be addressed were:

(i) What is the most efficient experimental design for the combination of DCE and TTO?
(ii) What is the best way to model the combined DCE and TTO data?

Experimental design is the methodology that is used to create the content and structure of the set of stimuli that is presented to the respondents. In our case this is the set of EQ-5D health states that will be shown to the respondents. Efficiency is about minimising the number of states and the number of respondents needed to get significant parameter estimates. The number of parameters that can be estimated in the model depends on the number of states that are included in the design. In order to measure X parameters the theoretical minimum number of different states that needs to be included in the design is X+1. However, using the minimum number of states does not mean that this will give you the best results. Including more pairs will give better results.

Orthogonality (i.e. attribute levels are independent), minimum overlap (i.e. minimum overlap of levels for each attribute) and level balance (i.e. levels of each attribute appear the same number of times) are all design optimisation criteria that are used to minimise the number of respondents that are needed. This does not mean that with a design that does not conform to these three criteria it is not possible to estimate a utility model, only that a more efficient way of collecting data might be possible (i.e.

needing fewer respondents). Including more respondents than the bare minimum will give better results. Existing experimental design algorithms could, in principle, be readily applied to a DCE or a TTO experiment. However, since our data is a combination of data from two distinct valuation tasks (i.e. LT-TTO and DCE), it is not clear cut what the "optimal design" is for such a hybrid approach. The optimization procedure of the experimental design for the hybrid should take the following into account:

(i) the number of health states in both the LT-TTO and DCE tasks,
(ii) the number of respondents to be included,
(iii) the selection of the sets of health states to be included in the LT-TTO and DCE tasks, and
(iv) the model that will be used to analyze the data.

The aim of this study was to develop an optimization algorithm for the creation of an experimental design for a LT-TTO/DCE hybrid study and to develop a model for the combination of LT-TTO and DC data (which is also needed for the optimization algorithm. We will describe the process of investigating how different combinations of sets of TTO and DCE questions perform in their potential to predict the mean and median values for the EQ-5D-5L utilities.

3.2 METHODS

Experimental design for DCE has been a topic that has received a lot of attention of the past few years (see for example[2-4]). On the contrary, little has been published on experimental design methods for TTO. This implied that for the DCE part of the study we could use design algorithm that was developed relatively recent (i.e. 2006-2007), whereas for the TTO part we needed to dig a little deeper. The overall design algorithm comprises the following steps:

(i) Use a simulation model to generate data given by respondent assuming certain behavior and differences
(ii) Generate an optimal Fedorov design for a (pre-specified) number of health states with blocks of 5 TTO questions per respondent and simulate the data for this design for N respondents.
(iii) Generate an efficient DCE design for a (pre-specified) number pairs of health states with blocks of 10 DCE questions per respondent and simulate the data for this design for N respondents.
(iv) Estimate a model on the combination of the TTO and DCE data based on the individuals from 1) creating data for questions created in steps 2) and 3)
(v) Compare the modeled results from step 4) with the underlying input.
(vi) Repeat steps 2) to 5) for different numbers of respondents and health states to gain information on how the numbers of respondents and states included in a study will affect the predictions of the saturation data.

Steps 1) to 4) of the algorithm are described in more detail below.

Step 1) The simulation model

A behavioral model is created based on assumptions of the heuristics used by respondents when completing the TTO and DCE tasks. The model captures that respondents differ in the shape of their value functions, their value for death, and their tendency to trade life years. Additionally they will be assumed to make random errors. At this stage we assume a simple linear model without interactions but with heterogeneity in the weights given to the various dimensions and heterogeneity in the positioning of the levels within the dimensions. This with Dirichlet distributions. Additionally, we assume that individuals make some errors when judging the health states. The weights for the various dimensions are 0.20 for mobility, 0.15 for self care, 0.1 for usual activities and 0.30 and 0.25 for pain/discomfort and anxiety / depression respectively. Within each dimension we assume equidistance between the levels on average. Values are positive and subtracted from 1. The subtracted value is multiplied with a random number from a lognormal distribution with expectation 1 and variance 0.1.

Step 2) The design for the LT-TTO

The goal of algorithmic design is to maximize the information about the parameters. In order to create an optimal experimental design for the LT-TTO we used a Federov algorithm[6,7]. The optimisation criterion we used was D-optimality, which seeks to minimize the determinant of the inverse of the matrix (X'X), or equivalently maximize the determinant of the information matrix X'X of the design. This criterion results in maximizing the differential Shannon information content of the parameter estimates.

For the 4C study it was decided that each respondent would answer 10 TTO questions. Because more than 10 TTO states need to be valued, the design needs to be blocked. We included the division of the health states into blocks of 10 each in our Federov algorithm. The algorithm therefore produces the optimal design for the total number of TTO states while simultanously optimising for blocks of 10 states.

Step 3) The design for the DCE

In the 3L DCE pilot the most frequently used design algorithms were compared and finally a Bayesian efficient design algorithm was selected as the most appropriate technique[1]. It was therefore decided to build on the experiences learned from the 3L pilot and use a so called "efficient design" algorithm for the DCE in the 4C pilot study. The method uses Monte Carlo simulation to derive a choice set based on a pre-specified utility model. The advantage of this approach is that it is less restrictive in the optimisation process. For example, one can incorporate orthogonality or level balance as design criteria, but does not need to. The use of priors on the pre-specified utility function is another advantage (especially since in the case of EQ-5D there is an abundance of data that could be used as prior). The parameter estimates of the (unrescaled) main effects DCE model from the 3L pilot were used as priors for the DCE design algorithm in this study.

We did not use the Bayesian efficient design algorithm that was used in the 3L pilot because of computational burden. This is because our design algorithm needs to optimize for both DCE and TTO, and the addition of an additional loop of iterations for the priors of the DCE design would make our optimization algorithm unwieldy. The efficient design algorithm we used to optimize the DCE uses the same D-optimality criterion as the Federov algorithm. The optimization procedure is different though, due to the inherently different nature of DC data.

Step 4) Estimate the utility model

For the designs created under steps 2) and 3) respondents will be simulated answering them. Subsequently the data will be used to estimate value functions which can be used to predict average and median responses for each health state. Value functions were estimated for the LT-TTO data using linear regression (OLS) and maximum likelihood estimation. For the DC data and the combination of the TTO and DCE data we used a maximum likelihood model. The details concerning the likelihood functions are presented in Appendix 3A.

The resulting value function for the combined TTO and DCE data from step 4) can be seen as a predictive model for the study design that was generated in steps 2) and 3). These predictions can subsequently be compared to the data from the simulated saturation dataset created under step 1).

A number of the variables used in the optimisation algorithm had been decided upon apriori for the 4C study. The number of respondents was set to 400 per country, each respondent will answer 10 DCE questions and 5 TTO questions. We assumed –for our base case simulation- that a total of 100 TTO states would be included and 200 pairs of DCE states. This means that effectively we'll have 20 observations per state/pair per study (i.e. 80 observations for the combined 4C data).

We start with simulating 25 of such studies and observe the variance in the estimations. Subsequently we increase the numbers of observations and observe to what extent the variance decreases. After that we play with the idea to increase the number of TTO's per individual and to increase the number of DCE's per individual. This aims to give us an idea of the added value of a DCE comparison vs a TTO question.

3.3 RESULTS

Our base case consisted of 100 health states for the LT-TTO, 200 pairs of health states for the DCE, and 1600 respondents (i.e. 4x400 as in the 4C study). The optimal Fedorov blocked design for the TTO in our base case simulation is shown in Appendix 3B.

Figure 3.1 presents the variance surrounding an example parameter (in this case the fourth level on mobility) when simulating 25 different data sets with varying numbers of respondents. We do this for TTO, TTO with DCE without correction parameter and TTO plus DCE with correction parameter (combination plus). The bad news is that we find that simply combining the likelihood from the DCE and the likelihood from the linear regression leads to unexpected results. The parameters of the DCE are much higher than the coefficients that were used to generate the utilities. This appears to be solved when including a simple scale parameter which is estimated simultaneously in the likelihood function. As may be expected, the variance after adding the DCE data is much smaller with the combination than with the TTO data only.

Assuming that the estimates from the combination approach with scale parameter will be used to estimate the value function, we may analyze what the decrease is in the variance when increasing the number of states in the TTO part or in the DCE part. Based on this analysis we see that (in terms of the decrease in the standard deviation of the estimates) adding a question to the DCE part decreases the variance with 0.58 times of what adding a TTO question does. Stated otherwise: in terms of precision, we estimate that adding 1.7 DCE is worth as much as adding one TTO (of course within the environment of all our assumptions).

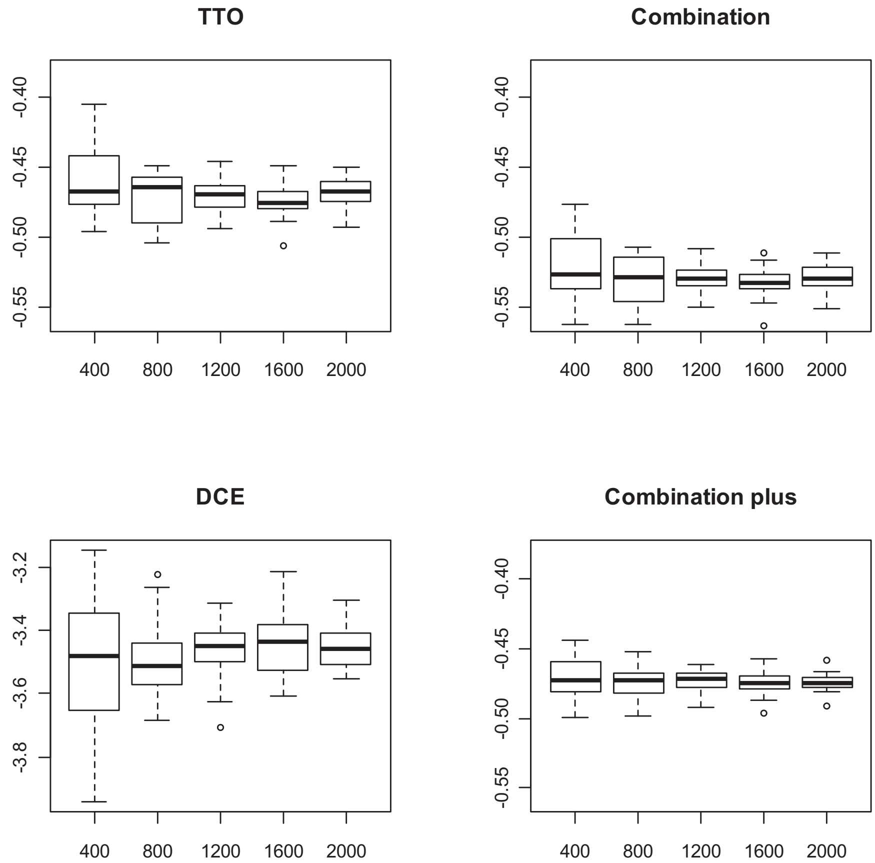

Figure 3.1. Estimation results for β_{14} using different models.

3.4 CONCLUSION

The results in this paper are part of work in progress. In this paper we described the development of the optimization algorithm for the experimental design of a DCE - TTO hybrid model. Although we have not yet determined the optimal design, we have shown how (and that) the algorithm works and this methodology can therefore be used to inform on the model specifications and associated experimental designs for the planned four country pilot study. After the data has been collected for the 4C study, we can use these to check and refine both the design algorithm and the model. The refined design algorithm and model can subsequently be used in the "official" EQ-5D-5L valuation studies.

In the mean time we have created a play-garden for analysts to address all kinds of issues. As a teaser we have calculated the value of a DCE question in comparison to a TTO question and conclude – in our view quite surprisingly – that 17 DCE's may be as valuable as 10 TTO's. Naturally, this estimate is conditional on all assumptions underlying the current calculations. It may be quite different when matters are not linear or in the presence of interactions. Other issues which may be addressed are the effects of different distributions of the position of death and the effects of tendencies not to trade.

As an aside, the comparison between the 4C-pilot data and the simulated data will allow us to check and refine our data simulation model. The ability to create a dataset via simulation that reasonably accurately matches the observed data can be seen as a validity check of the behavioral model that was used to simulate the data. This in turn might prove to be valuable for understanding and explaining some of the key aspects of how the respondents complete the DCE and TTO tasks.

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APPENDIX 3A
DETAILS CONCERNING THE LIKELIHOOD FUNCTIONS

For the linear regression model we assume a linear equation between a value v and dummies d_{ij}: $f(v_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{2\sigma^2} \right)$

We may write the log of the likelihood of the data as observed as:

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

and we may use a Newton Rhapson algorithm to estimate the parameters using the following derivatives and hessian.

$$\frac{\partial \text{loglik}}{\partial \sigma^2} = -\frac{N}{2\sigma^2} + \sum_{i=1}^{N} \frac{\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{2\sigma^4}$$

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

$$\frac{\partial^2 \text{loglik}}{\partial (\sigma^2)^2} = \frac{N}{2\sigma^4} - \sum_{i=1}^{N} \frac{\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{\sigma^6}$$

$$\frac{\partial^2 \text{loglik}}{\partial (\sigma^2) \partial \beta_k} = -\sum_{i=1}^{N} \frac{d_{ik}\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{\sigma^4}$$

$$\frac{\partial \text{loglik}}{\partial \beta_k \delta \beta_l} = -\sum_{i=1}^{N} \frac{d_{ik} d_{il}}{\sigma^2}$$

$$\frac{\partial^2 \text{loglik}}{\partial \beta_k \partial (\sigma^2)} = -\sum_{i=1}^{N} \frac{d_{ik}\left(v_i - \sum_{j=1}^{nd} \beta_j d_{ij} \right)^2}{\sigma^4}$$

When considering a discrete choice model between a health state on the left vs a health state on the right, we may write:

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

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

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

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

and we may write the likelihood function and its derivatives as:

$$likelihood = \prod_{i=1}^{Npair} \left(\frac{1}{\left(1 + \exp\left(-\sum_{j=1}^{nd} \beta_j \left(d^i_{lj} - d^i_{rj}\right)\right)\right)} \right)^{N^i_{LGTR}} \cdot \left(\frac{\exp\left(-\sum_{j=1}^{nd} \beta_j \left(d^i_{lj} - d^i_{rj}\right)\right)}{\left(1 + \exp\left(-\sum_{j=1}^{nd} \beta_j \left(d^i_{lj} - d^i_{rj}\right)\right)\right)} \right)^{N_{RGTL}}$$

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

$$\frac{\partial Loglik}{\partial \beta_k} = \sum_{i=1}^{Npair} . \frac{-N^i_{LGTR} \exp(-\beta' \Delta d_i) - N^i_{RGTL}}{(1 + \exp(-\beta' \Delta d_i))} \Delta d_{ik}$$

$$\frac{\partial^2 Loglik}{\partial \beta_k \partial \beta_l} = \sum_{i=1}^{Npair} \frac{\left(-N^i_{LGTR} + N^i_{RGTL}\right) \exp(-\beta' \Delta d_i)}{(1 + \exp(-\beta' \Delta d_i))^2} \Delta d_{ik} \Delta d_{il}$$

The combination of the two may be seen as a simple product or one may want to use a correction constant between the sets of beta's. We try both. The following formulas were used to combine both sets of data.

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

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

$$\frac{\partial \text{loglik}}{\partial \sigma^2} = -\frac{N}{2\sigma^2} + \sum_{i=1}^{N}\frac{\left(v_i - \sum_{j=1}^{nd}\beta_j d_{ij}\right)^2}{2\sigma^4}$$

$$\frac{\partial \text{loglik}}{\partial \beta_k} = \sum_{i=1}^{N}\frac{d_{ik}\left(v_i - \sum_{j=1}^{nd}\beta_j d_{ij}\right)}{\sigma^2} + \sum_{i=1}^{Npair}.\frac{-N^i_{LGTR}\exp(-\theta\beta'\Delta d_i) - N^i_{RGTL}}{(1+\exp(-\theta\beta'\Delta d_i))}\theta\Delta d_{ik}$$

$$\frac{\partial \text{loglik}}{\partial \theta} = \sum_{i=1}^{Npair}.\frac{-N^i_{LGTR}\exp(-\theta\beta'\Delta d_i) - N^i_{RGTL}}{(1+\exp(-\theta\beta'\Delta d_i))}\beta'\Delta d_i$$

And for the hessian:

$$\frac{\partial^2 \text{loglik}}{\partial(\sigma^2)^2} = \frac{N}{2\sigma^4} - \sum_{i=1}^{N}\frac{\left(v_i - \sum_{j=1}^{nd}\beta_j d_{ij}\right)^2}{\sigma^6}$$

$$\frac{\partial^2 \text{loglik}}{\partial(\sigma^2)\partial\beta_k} = -\sum_{i=1}^{N}\frac{d_{ik}\left(v_i - \sum_{j=1}^{nd}\beta_j d_{ij}\right)^2}{\sigma^4}$$

$$\frac{\partial \text{loglik}}{\partial\beta_k\delta\beta_l} = -\sum_{i=1}^{N}\frac{d_{ik}d_{il}}{\sigma^2} + \sum_{i=1}^{Npair}\frac{\left(-N^i_{LGTR} - N^i_{RGTL}\right)\exp(-\theta\beta'\Delta d_i)}{(1+\exp(-\theta\beta'\Delta d_i))^2}\theta^2\Delta d_{ik}\Delta d_{il}$$

$$\frac{\partial^2 \text{loglik}}{\partial\beta_k\partial(\sigma^2)} = -\sum_{i=1}^{N}\frac{d_{ik}\left(v_i - \sum_{j=1}^{nd}\beta_j d_{ij}\right)^2}{\sigma^4}$$

$$\frac{\partial^2 \text{loglik}}{\partial\theta^2} = \sum_{i=1}^{Npair}.\frac{N^i_{LGTR} - N^i_{RGTL}}{(1+\exp(-\theta\beta'\Delta d_i))^2}\exp(-\theta\beta'\Delta d_i)(\beta'\Delta d_i)^2$$

$$\frac{\partial^2 \text{loglik}}{\partial\beta_k\partial\theta} = \sum_{i=1}^{Npair}\left(\frac{-N^i_{LGTR}\exp(-\theta\beta'\Delta d_i) - N^i_{RGTL}}{(1+\exp(-\theta\beta'\Delta d_i))} + \frac{\left(N^i_{LGTR} - N^i_{RGTL}\right)\exp(-\theta\beta'\Delta d_i)}{(1+\exp(-\theta\beta'\Delta d_i))^2}\beta'\Delta d_i\theta\right)\Delta d_{ik}$$

$$\frac{\partial^2 \text{loglik}}{\partial(\sigma^2)\partial\theta} = 0$$

APPENDIX 3B OPTIMAL FEDEROV DESIGN FOR TTO

TTO	MO	SC	UA	PD	AD
	1	4	4	1	1
	4	1	4	4	1
block 1	4	1	1	1	3
	5	5	5	2	5
	2	2	5	5	5
	4	4	1	1	1
	1	1	1	4	1
block 2	2	5	5	4	1
	5	5	2	5	3
	3	3	3	2	5
	3	1	1	4	1
	1	3	4	4	1
block 3	5	5	4	4	3
	1	4	1	1	5
	4	1	4	1	5
	2	5	5	2	1
	5	5	2	5	1
block 4	2	1	1	1	3
	5	2	5	2	5
	1	4	4	4	5
	3	1	4	1	1
	4	4	1	4	1
block 5	1	4	1	1	3
	5	2	2	2	5
	1	1	1	4	5
	1	1	4	1	1
	5	5	5	5	1
block 6	5	2	2	2	3
	2	5	5	2	5
	2	2	2	5	5
	1	1	4	4	1
	5	3	2	5	1
block 7	5	2	5	2	3
	4	1	1	4	5
	2	5	4	5	5
	1	2	1	2	1
	4	5	5	3	1
block 8	5	2	2	5	1
	2	2	5	5	3
	2	5	2	5	5
	2	5	2	2	1
	5	2	5	2	1
block 9	2	2	2	5	1
	1	1	2	1	5
	2	5	5	5	5
	1	4	1	4	1
	5	4	5	5	1
block 10	4	1	3	4	3
	4	4	1	1	4
	1	1	4	1	5

TTO	MO	SC	UA	PD	AD
	4	1	4	1	1
	3	3	3	3	3
block 11	4	4	1	1	5
	1	1	4	4	5
	5	5	5	5	5
	1	4	1	1	1
	4	1	4	3	1
block 12	1	1	1	4	4
	4	4	4	1	5
	5	5	2	5	5
	1	1	1	1	1
	2	5	5	5	1
block 13	4	4	1	4	4
	1	4	4	1	5
	4	1	4	4	5
	3	3	2	1	1
	5	2	5	5	1
block 14	2	5	5	2	3
	5	5	2	2	5
	1	1	4	3	5
	4	4	4	1	1
	1	1	4	3	1
block 15	1	4	1	4	3
	4	1	1	1	5
	4	5	5	5	5
	5	5	2	2	1
	2	2	5	5	1
block 16	1	4	4	1	3
	3	1	4	1	5
	1	4	1	4	5
	5	5	5	2	1
	4	1	1	4	1
block 17	1	1	4	1	3
	3	3	3	3	5
	5	2	5	5	5
	4	1	1	1	1
	2	2	3	5	3
block 18	2	5	2	2	5
	2	2	5	2	5
	5	2	2	5	5
	5	2	2	2	1
	2	5	3	5	1
block 19	5	5	5	2	4
	5	2	5	5	4
	4	4	1	4	5
	2	2	5	2	1
	2	5	2	5	1
block 20	5	5	2	2	2
	1	1	1	1	5
	5	2	3	5	5