Available online at www.sciencedirect.com

SciVerse ScienceDirect

journal homepage: www.elsevier.com/locate/jval

Learning Effects in Time Trade-Off Based Valuation of EQ-5D Health States

Liv Ariane Augestad, MD[1,*], *Kim Rand-Hendriksen, Cand. Psychol, MSc*[1], *Ivar Sønbø Kristiansen, MD, MPH, PhD*[2], *Knut Stavem, MD, MPH, PhD*[1,3,4]

[1]*Health Services Research Centre, Akershus University Hospital, Lørenskog, Norway;* [2]*Institute of Health Management and Health Economics, University of Oslo, Oslo, Norway;* [3]*Department of Pulmonary Medicine, Akershus University Hospital, Lørenskog, Norway;* [4]*Medical Faculty, Faculty Division, Akershus University Hospital, University of Oslo, Lørenskog, Norway*

A B S T R A C T

Objectives: In EuroQol five-dimensional questionnaire valuation studies, each participant typically assesses more than 10 hypothetical health states by using the time trade-off (TTO) method. We wanted to explore potential learning effects when using the TTO method, that is, whether the valuations were affected by the number of previously rated health states (the sequence number). **Methods:** We included 3773 respondents from the US EQ-5D valuation study, each of whom valued 12 health states (plus unconscious) in random order. With linear regression, we used sequence number to predict mean and standard deviations across all health states. We repeated the analysis separately for TTO responses indicating a state better than death and a state worse than death. Each TTO value requires a specific number of choice iterations. To test whether respondents used fewer iterations with experience, we used linear regression with sequence number as the independent variable and number of iterations as the dependent variable. **Results:** Mean TTO values were fairly stable across the sequence number, but analyzing state better than death and state worse than death values separately revealed a tendency toward more extreme values: state better than death values increased by 0.02, while state worse than death values decreased by 0.21 ($P < 0.0001$) over the full sequence. The standard deviations increased slightly, while the number of choice iterations was the same over the sequence number. The findings were stable across the levels of health state severity, age, and sex. **Conclusions:** TTO values become more extreme with increasing experience. Because of the randomized valuation order, these effects do not bias specific health states; however, they reduce the overall validity and reliability of TTO values.

Keywords: learning effect, preferences, time trade-off, valuation study.

Introduction

Several methods are available to measure preferences for health states. Ideally, the elicitation method should not affect the responses, but there is ample evidence that it does [1,2]. Gaining experience with a specific elicitation method may also influence responses. A study examining willingness to pay reported lower willingness to pay and reduced variance as respondents gained experience with the valuation method [3]. The time trade-off (TTO) method is frequently used to elicit health state values [4,5]. It is used to identify the point of indifference between a fixed length of life in an impaired health state and a shorter life span in perfect health. Utilities are calculated as time in perfect health divided by time in the target health state. The TTO method is a challenging cognitive task, and it is conceivable that gaining experience with the method may influence the resulting values.

The EuroQol five-dimensional (EQ-5D) questionnaire is one of the most frequently used multiattribute utility instruments, and it describes composite health states along five dimensions: mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. Each dimension has three levels: no health problems (level 1), moderate health problems (level 2), and extreme health problems (level 3). The EQ-5D thus describes 3^5 (=243) health states [6]. The TTO method is dominant in EQ-5D valuation studies, in which respondents typically value 13 to 17 health states [7].

In a Polish EQ-5D TTO valuation study, each participant valued 23 health states but there were no differences between population means or variances for early valuations (6th–17th) and late valuations (18th–23rd) [8]. The first valuations (1st–5th) were considered "warm-up exercises" and did not include the same sample of health state profiles as the rest of the TTO tasks. To our knowledge, this is the only study that has examined the effect of increasing experience with the TTO exercise on the valuations. It is unknown whether there are effects earlier in the valuation process (1st–5th valuations) or whether experience with the TTO method affects the distribution of the responses in other ways than the mean.

In the present study, we use the term *learning effect* for all systematic differences in responses as a function of increasing experience with the TTO method. Learning effect thus refers to the TTO method, and not learning from valuing specific health states. This is not only

* *Address correspondence to:* Liv Ariane Augestad, Health Services Research Centre, Akershus University Hospital, 1478 Lørenskog, Norway.

E-mail: livariane@gmail.com; liv.ariane.augestad@ahus.no.

1098-3015/$36.00 – see front matter Copyright © 2012, International Society for Pharmacoeconomics and Outcomes Research (ISPOR). Published by Elsevier Inc.

doi:10.1016/j.jval.2011.10.010

restricted to an improved understanding of the method but may also include strategies enabling the respondent to finish the task quickly and avoid discomfort, exhaustion, boredom, and so on.

The primary objective of the study was to identify potential learning effects by analyzing the distribution of respondents' values as a function of the number of previously valued health states with the TTO task (sequence number). Because the TTO procedure is a complex task, one might expect that a part of the variance in TTO responses is attributable to respondents not understanding the task (noise) and that this noise would be reduced with increasing experience with the valuation task. Hence, an expected learning effect was a reduction in SD for single health states. The secondary objective was to test whether potential learning effects were stable for health states of different severity, as described by the EQ-5D system, and whether they were stable for respondents across age and sex.

Methods

Material

We used data collected through face-to-face interviews in a large US EQ-5D valuation study and the same exclusion criteria as in the original study [9], after which 3773 respondents were included in our analyses. Each respondent valued 13 health states in a randomized order by using the TTO method. In total, 42 health states were valued. For further details, we refer to the original valuation study [9].

Valuation task

Each TTO valuation started by asking the respondent whether he or she (a) would prefer to live 10 years in the presented (impaired) EQ-5D health state, (b) would prefer immediate death, or (c) considered that (a) and (b) were equally (un)preferable. If the respondent chose alternative (c), the valuation for that particular health state was over and the TTO value was set to 0. The method for subsequent valuation was different when choosing alternative (a)—states considered better than death (SBD) and alternative (b)—states considered worse than death (SWD). The interviewers used props to visualize the different lengths of life A and life B.

SBD

The aim of the SBD task was to reach a point of indifference between life A (10 years in the impaired EQ-5D health state) and a reduced number of years in life B (perfect health). Throughout the SBD task, life A was held constant at 10 years while life B was varied according to the choices of the respondent (Fig. 1). At equilibrium, the TTO value (u) was calculated by dividing the number of years in perfect health (t) by the number of years in the target health state: $u = t/10$. The upper value is thus restricted to 1, the same as full health.

SWD

If the respondent preferred life B in the initial choice task, that is, stated that the target health state was worse than death, the choice task proceeded in a different manner. Life A was still 10 years but a composite life of the target health state (x years) *and* perfect health ($10 - x$ years), followed by immediate death. For an SWD valuation, life B was always set at 0 years. The aim of the task was to reach a point of indifference between immediate death and life A, in which time in target health state and time in perfect health were varied simultaneously (Fig. 1). The TTO value (u) was calculated as the negative number of years in perfect health divided by the number of years in the target health state: $u = -t/(10 - t)$.

Elicited in this way, SWD values have no lower boundary, the lowest possible value depends on the smallest tradable unit of time, which, in this case, was 0.25 years (3 months) [7]. Therefore, the lowest possible score was -39 or $-9.75/(10 - 9.75)$.

In previous EQ-5D questionnaire TTO valuation studies, values for SWD had been transformed to restrict the scale to -1 [10]. In this study, we used the most frequently applied transformation method [7]:

$$u = \frac{-t}{10 - t}$$

$$u' = \frac{u}{1 - u} = \frac{-t}{10}$$

Sensitivity analyses were performed by using an alternative transformation algorithm [11], in which the TTO score is simply divided by the positive of the lowest possible value: in this case, 39:

$$u' = \frac{u}{39} = \frac{-t}{39(10 - t)}$$

Analyses

We plotted all TTO values as a function of the sequence number, regardless of the target health state, and calculated the mean TTO value within each sequence number. We used this mean TTO value as the dependent variable and sequence number as the independent variable in ordinary least squares (OLS) regression. Because SBD and SWD values were elicited differently, the learning effects might also be different. We therefore performed separate analyses for the two categories of responses.

To test whether SD decreased with increasing TTO experience, we needed a measure of agreement that was independent of the varying severity of the different health states. To achieve this, we first calculated the means of the TTO values for each of the 42 health states within each sequence number. For each single TTO valuation, we then subtracted the corresponding health state mean. We thus obtained an adjusted mean of zero for each health state, without altering the variation around the mean. We then calculated the SD around the adjusted mean of zero for each sequence number. Finally, we used OLS regression, with the 13 SD values as the dependent variable and the sequence number as the independent variable. Converging values should then translate into a negative slope in the regression model.

Using the "ping-pong" procedure, different TTO values require different number of choice iterations before the respondent reaches the point of indifference. To test whether respondents chose values requiring less choice iteration with cumulative experience, we created a variable corresponding to the number of choice task iterations needed to reach each TTO value. In linear regression, we used this variable as the dependent variable and sequence number as the independent variable.

To test whether learning effects were different for health states of different severity, we stratified the health states into three groups (14 states in each) by mean TTO values and replicated all the previous analyses for these. To test whether learning effects differed by sex, we repeated the previous OLS regression analyses with sequence number, sex, and variable sex $\times$ sequence number interaction as independent variables. We also repeated all the above analyses separately for three age groups (<35, 35–55, and >55 years). For analyses regarding sex and age, we chose a 5% significance level by using two-sided tests.

To test whether learning effects differed by the levels of education, we repeated the previous regression analyses with the material split into five groups according to the level of education (in years of education: <9, 9–11, 12, 13–15, and >15). The analyses were performed by using 12-year education as a baseline, with one dummy variable representing each of the four other education groups, a main sequence number variable, and sequence number $\times$ education group interaction terms.