Immediate death: not so bad if you discount the future, but still worse than it should be.

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Abstract

Background: Use of Discrete Choice Experiments (DCEs) as a stand-alone valuation method requires anchoring latent scale DCE estimates on the 0-1 QALY scale, usually either through tasks involving choices between immediate death and various impaired health states, or between health states with varying durations of life. We sought to determine which anchoring approach aligns best with the composite Time Trade-Off (cTTO) method.

Methods: A sample of 970 respondents from Trinidad and Tobago completed a DCE with duration survey. Tasks involved choosing between two lives with identical durations, followed by a third option, representing either full health for a number of years or immediate death. The data were analysed using mixed logit models, both with and without exponential discounting for time preferences. The models were anchored via full health and immediate death tasks.

Results: When imposing linear time preferences, the utility of immediate death was estimated to be -2.1 (95% CrI -3.2 to -1.2) vs. -0.28 (95% CrI -0.47, -0.10) when allowing for non-linear time preferences. Under linear time preferences, the predicted health-state values anchored on duration range between -1.03 and 1 compared to 0.34 and 1 when anchored on immediate death. Under non-linear time preferences, the predicted values anchored on duration ranged between -0.54 and 1 vs. -0.22 and 1 when anchored on immediate death. In the model accounting for non-linear time preferences, the estimated discount parameter was 23% with (95% CrI 22% to 25%)

Conclusions: The non-zero discount parameter provides evidence of non-linear time preferences. The non-linear time preferences anchored on duration provided the closest match to the benchmark EQ-VT cTTO values in Trinidad and Tobago, which ranged from -0.6 to 1. These findings suggest that DCE with duration can provide similar values to cTTO provided that nonlinear time preferences are accounted for, and anchoring is based on duration.

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Introduction

Quality-adjusted life years are a key component in economic evaluations in many countries (1-4), and typically rely on instruments such as the EQ-5D-5L (5), SF-6D (6), or HUI3 (7) to elicit health utilities. These instruments require a value set that specifies the population utility associated with each health state captured by the instrument. Discrete choice experiments have emerged as a promising approach to creating such value sets, as they can be done online and do not need to be interviewer-administered (8, 9). This makes them an attractive alternative to cTTO and standard gamble, both of which need to be administered by a trained interviewer.

When respondents choose between two health states without duration, preferences can be inferred on a latent scale, i.e. up to a linear transform. Some additional information is required to anchor the utilities on the full-health – dead scale (where full health has a utility of 1 and being dead has a utility of zero). These anchors can be either external (12, 13) or based on additional discrete choice tasks. This latter option is the focus of this paper. There are two types of additional tasks that can be used to anchor the latent utilities: a discrete form of TTO anchoring which involves trading off an impaired health state of a specified duration with full health for a shorter duration, or trading off impaired health states of a specified duration with immediate death.

The latter has been widely used (8, 9), however there is evidence that immediate death is not interpreted in the same way as “a health state of duration zero”, even though theoretically both should have a utility of zero (14). In particular, immediate death has been reported to have a much lower utility than a state of duration zero (11, 15). This finding is consistent with qualitative findings from time trade-off interviews, which suggest that there is both a discontinuity in preferences as durations approach zero (16, 17), as well as heterogeneity in how people interpret immediate death.

In dealing with either of these issues, a third issue must be contended with: time-preferences are non-linear. There is empirical evidence that respondents discount future health status in favour of improved health now (18, 19). However, estimating this discount rate requires careful selection of discrete choice tasks in order to make the parameter identifiable (20).

An important limitation in previous work exploring anchoring on immediate death is that the DCE tasks were not designed to permit estimation of the discount parameter. It is therefore currently unknown whether anchoring latent utilities from DCEs on immediate death remains problematic when incorporating discounting into the estimation procedure.

We previously reported on two valuation studies of the EQ-5D-5L in Trinidad & Tobago. The first valuation study used the international EQ-5D-5L EQ-VT valuation protocol based on composite time trade-off (cTTO) tasks (21), while the second used DCE with duration protocol (19, 22, 23) that permits the estimation of non-linear time preferences, and compared the results with that those obtained using the EQ-VT valuation protocol (24).

In this work, we use data collected in the Trinidad & Tobago DCE with duration valuation study to examine whether immediate death continues to have a lower utility than a state of duration zero after accounting for discounting. We compute value sets anchoring on a duration of zero and anchoring on immediate death, and examine how well the range of the value sets agrees with the range of the value set based on cTTO (24), in order to inform recommendations on how to anchor latent scale DCE utilities.

Methods

Population: We used an existing sample of 970 respondents included in the Trinidad and Tobago DCE valuation study (25). This study used quota sampling to achieve a population that was representative of the general population in terms of age, sex and geography. Recruitment was through a panel company, which used both an internet panel (emailed links to the survey) and recruitment in public places (e.g. libraries, transit hubs) with survey completion done on the recruiter's laptop.

Task types: Each respondent completed one set of 18 split triplets (26), 15 of which involved trade-offs with full-health and 3 of which involved trade-offs with immediate death. Each triplet began with a pair of health states of equal duration (life A and life B), from which the respondent was asked to choose their preference. To simplify the task, life A and life B differed in just 3 of the 5 EQ-5D-5L dimensions; the other two dimensions were the same in life A and life B.

Regardless of the stated preference, in the second half of the triplet life A was blurred and the respondent was asked to choose between life B and life C. In those split triplets involving tradeoffs with full health, life C was defined as full health but with a shorter duration than life B; this choice is thus a discrete version of a traditional TTO task. In those split triplets involving tradeoffs with immediate death, life C was immediate death.

DCE design: A near-orthogonal design was used initially; the responses to which (n=211) were analysed to create a more efficient design using the TPC-QD software package (20). The design was further updated at intervals of 200 respondents until the priors used to generate the design did not change substantially between updates. Durations were whole years from 1 up to and including 15, with an additional duration of 6 months. Each design contained 10 subdesigns with 18 split triplets as described above. Respondents were randomly assigned to one of the 18 split triplets, with the order of lives A and B also randomly assigned.

Analytic plan: Letting U_{ijt} be the latent utility for respondent i valuing health state j with a duration t, we assume a mixed logit model, i.e.,

$$U_{ijt} = X_j \beta_i^* D(t;\rho) + \beta_{ip+1}^* \mathrm{I}(\text{state j is immediate death}) + \sigma\epsilon_{ijt}$$

where X_j is a p-dimensional row vector of attributes of health state j whose first element is 1 to provide an intercept, ϵ_{ijt} ~iid Gumbel, $\beta_i^* \sim MVN(\beta^*, \Sigma^*{}_\beta)$, I() denotes an indicator function, and $D(t;\rho)$ is the discounted duration under exponential discounting with discount parameter ρ, i.e. $D(t;\rho) = \frac{1-exp(\rho t)}{exp\{\rho\}-1}$ for ρ >0 and D(t; ρ) = t for ρ =0.

We fitted two models. The first assumed no discounting, i.e. ρ =0, while the second used a Uniform(0,1) prior for ρ.

We assumed a main effects functional form for the design matrix, specifically X_j=(1,$MO2_j$, $MO3_j$, $MO4_j$, $MO5_j$, $SC2_j$, $SC3_j$, $SC4_j$, $SC5_j$, $UA2_j$, $UA3_j$, $UA4_j$, $UA5_j$, $PD2_j$, $PD3_j$, $PD4_j$, $PD5_j$, AD2$_j$, AD3$_j$, AD4$_j$, AD5$_j$), where MO2$_j$, MO3$_j$, MO4$_j$, MO5$_j$ are indicators (0=no, 1=yes) for whether mobility in health state j is at level 2, 3, 4 or 5 respectively, and similarly for self-care, usual activities, pain/discomfort, and anxiety/depression.

Models were estimated using OpenBugs, using 3 chains, a burn-in of 50000 and 50000 draws from the posterior distributions. Convergence was evaluated based on inspection of the chains and diagnostics proposed by Geweke (27) . The BUGS models, including the exact specification of the prior distributions, are included in the online supplemental.

The fitted models yield estimates of $\Sigma_{\beta}^{*}/\sqrt{2}\sigma$, $\beta = \beta^{*}/\sqrt{2}\sigma$, and ρ. To anchor the utilities to the full health-dead scale, we have two options. Option 1 is to assume that immediate death has a utility of zero, so that $\beta_1^{*} - \beta_{p+1}^{*} = 1$; it then follows that $\beta_1 - \beta_{p+1} = 1/\sqrt{2}\,\sigma$ so that $\beta^{*} = \beta/(\beta_1 - \beta_{p+1})$. Option 2 is to note that since full health has a utility of 1 by definition, i.e. β_1^{*}=1, and thus $\beta_1 = 1/\sqrt{2}\sigma$ so $\beta^{*} = \beta/\beta_1$. We anchored the utilities using each option in turn.

Results

As can be seen from Figure 1 and Table 1, both the choice of anchor and the choice of time preferences affect the coefficients.

When time preferences were assumed to be linear and anchoring was on duration, immediate death had a posterior mean disutility of -2.1 (95% CrI -3.2 to -1.2). This increased to -0.28 (95% CrI -0.47, -0.10) when allowing for non-linear time preferences.

Time preferences were not linear; the estimated discount rate parameter has a posterior mean of 23.4% with 95% CrI 21.7% to 25.1%. Assuming linear time preferences (i.e., fixing the discount parameter at zero) generally led to smaller disutilities when anchoring on immediate death (Figure 1, black vs. green lines), while it led to larger disutilities when anchoring on a duration of zero (Figure 1, red vs. blue lines).

Anchoring on immediate death led to smaller disutilities than anchoring on zero duration regardless of whether or not time preferences were assumed to be linear (Figure 1; linear: black vs. red; non-linear: green vs. blue), although the effect was more pronounced under linear time preferences. See Table 1 for tabulated regression coefficients.

Furthermore, when time preferences were assumed to be linear and anchoring was on duration, immediate death had a posterior mean disutility of -2.1 (95% CrI -3.2 to -1.2). This increased substantially to -0.28 (95% CrI -0.47, -0.10) on when allowing for non-linear time preferences (Table 1).

Table 1: Regression coefficients (Standard Errors) under linear and non-linear time preferences, and with anchoring on either immediate death or duration

	Linear time preferences		Non-linear time preferences	
	Anchored on		Anchored on	
	Immediate Death	Duration	Immediate Death	Duration
Mobility level 2	-0.021 (0.003)	-0.065 (0.011)	-0.025 (0.005)	-0.032 (0.007)
Mobility level 3	-0.048 (0.005)	-0.146 (0.019)	-0.075 (0.007)	-0.095 (0.009)
Mobility level 4	-0.095 (0.009)	-0.290 (0.035)	-0.169 (0.012)	-0.215 (0.013)
Mobility level 5	-0.153 (0.015)	-0.469 (0.052)	-0.284 (0.018)	-0.361 (0.018)
Self-care level 2	-0.026 (0.004)	-0.080 (0.013)	-0.031 (0.006)	-0.039 (0.007)
Self-care level 3	-0.037 (0.004)	-0.115 (0.016)	-0.057 (0.007)	-0.072 (0.008)
Self-care level 4	-0.084 (0.008)	-0.256 (0.030)	-0.142 (0.010)	-0.181 (0.011)
Self-care level 5	-0.120 (0.011)	-0.369 (0.044)	-0.223 (0.015)	-0.283 (0.014)
Usual Activities level 2	-0.023 (0.005)	-0.069 (0.010)	-0.017 (0.006)	-0.022 (0.007)
Usual Activities level 3	-0.037 (0.006)	-0.111 (0.013)	-0.045 (0.007)	-0.058 (0.008)
Usual Activities level 4	-0.069 (0.008)	-0.210 (0.022)	-0.106 (0.009)	-0.135 (0.010)
Usual Activities level 5	-0.098 (0.011)	-0.300 (0.031)	-0.166 (0.011)	-0.210 (0.012)
Pain/Discomfort level 2	-0.029 (0.004)	-0.089 (0.014)	-0.046 (0.006)	-0.059 (0.007)
Pain/Discomfort level 3	-0.046 (0.005)	-0.140 (0.018)	-0.078 (0.007)	-0.099 (0.008)
Pain/Discomfort level 4	-0.101 (0.010)	-0.308 (0.037)	-0.181 (0.013)	-0.230 (0.013)
Pain/Discomfort level 5	-0.153 (0.015)	-0.469 (0.054)	-0.287 (0.020)	-0.365 (0.019)
Anxiety/Depression level 2	-0.030 (0.004)	-0.093 (0.013)	-0.042 (0.006)	-0.053 (0.007)
Anxiety/Depression level 3	-0.060 (0.006)	-0.184 (0.025)	-0.100 (0.008)	-0.127 (0.009)
Anxiety/Depression level 4	-0.114 (0.010)	-0.349 (0.044)	-0.205 (0.014)	-0.260 (0.015)
Anxiety/Depression level 5	-0.136 (0.012)	-0.418 (0.052)	-0.255 (0.017)	-0.324 (0.017)
Immediate Death Utility of 55555 (95% CrI)	n/a	-2.102 (0.538)	n/a	-0.275 (0.095)

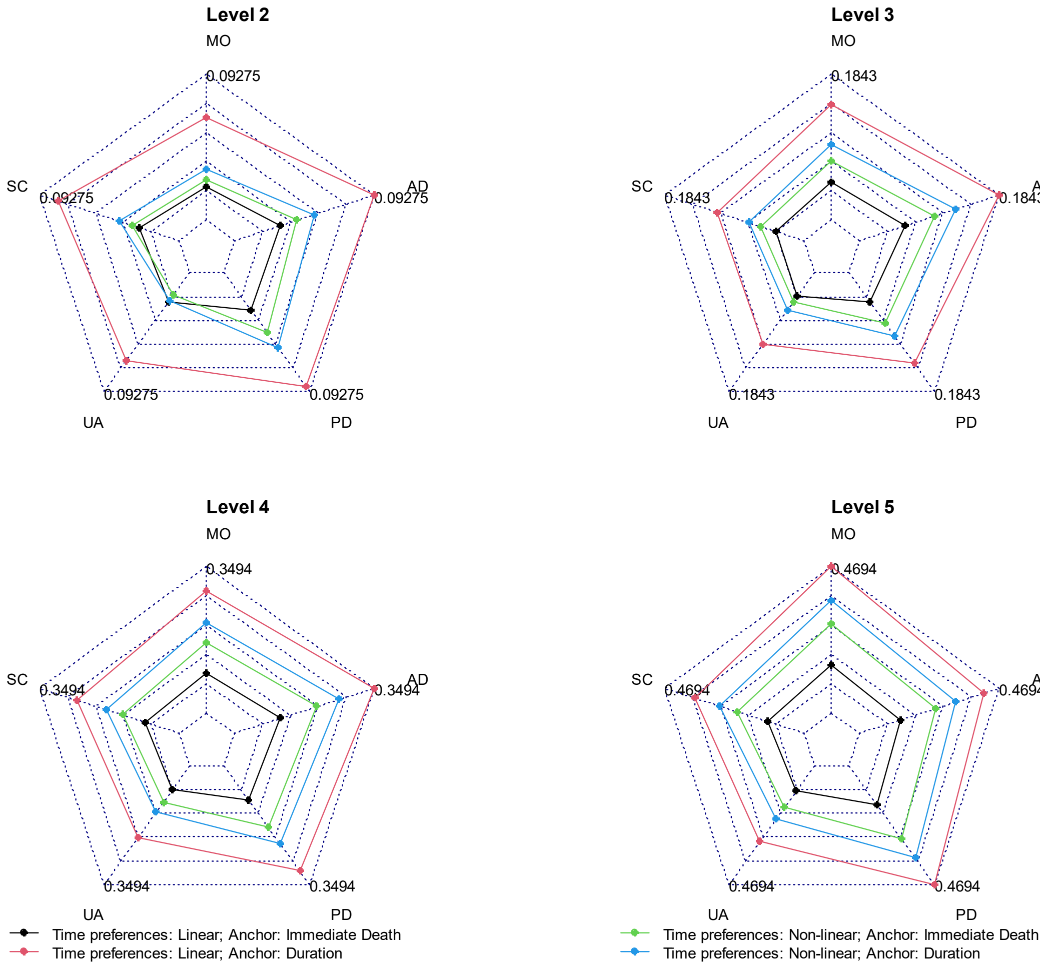

Figure 1: Radar plot of scaled disutilities from the mixed logit models with and without non-linear time preferences, and with anchoring on either immediate death or duration

The worst health state had an estimated utility of 0.34 (95% CrI 0.20, 0.44) with linear time preferences anchored on immediate death, -1.03 (95% CrI -1.54, -0.65) with linear time preferences anchored in duration, -0.21 (95% CrI -0.37, -0.08) for non-linear time preferences anchored on immediate death, and -0.54 (95% CrI -0.69, -0.41) for non-linear time preferences anchored on duration (Figure 2). For comparison, the reported utility for the worst health state using cTTO was -0.61. Correspondence between the health state utilities under cTTO and DCE are shown in Figure 3, with non-linear time preferences anchored on duration providing the closest correspondence.

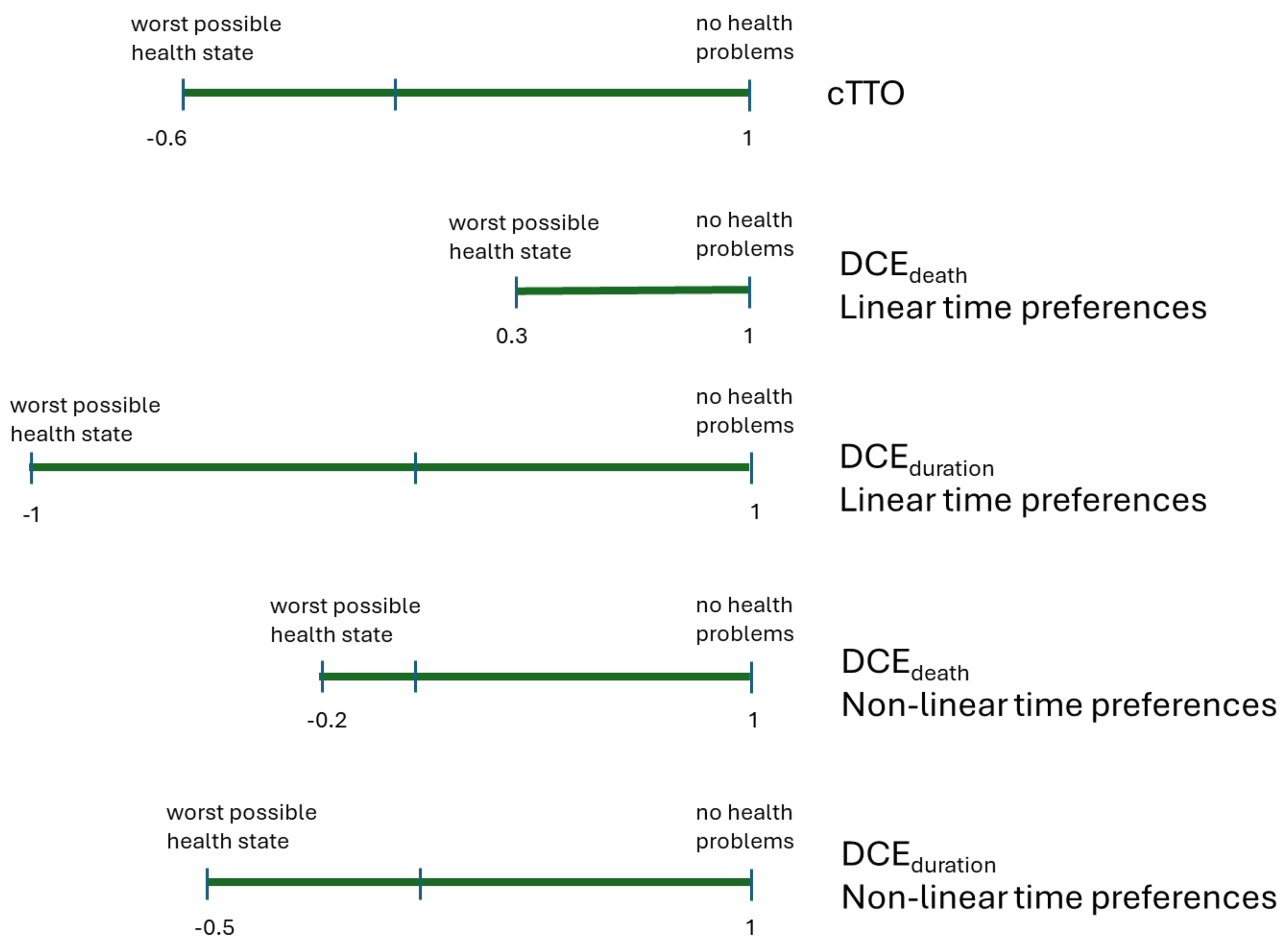

Figure 2: Length of the QALY scale under different time preferences and anchor choices

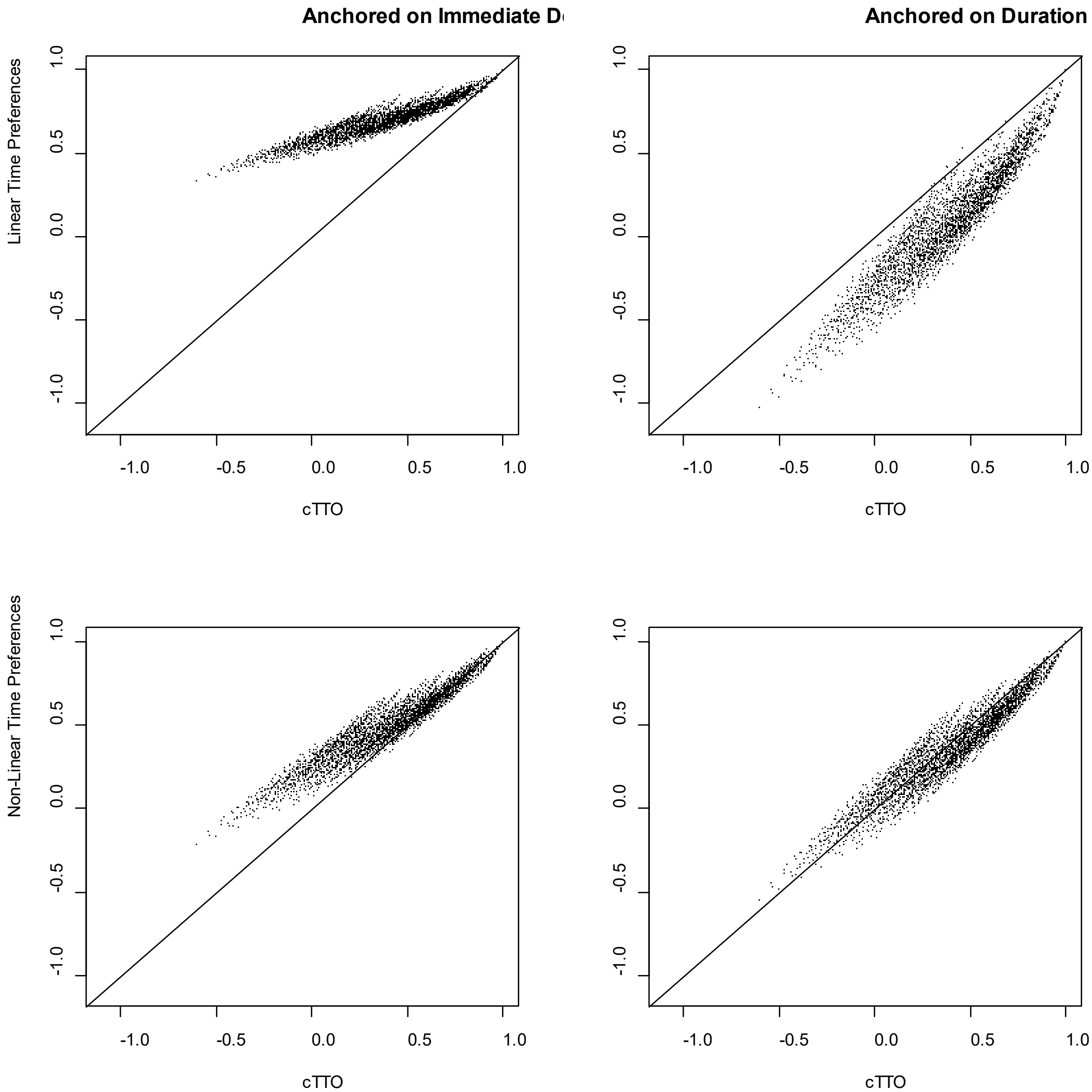

Figure 3: Comparison of DCE-based tariffs to the cTTO tariff

Discussion

A unique contribution of this paper is that we have compared anchoring on duration vs. anchoring on immediate death while accounting for non-linear time preferences. Our findings in a general population sample from Trinidad and Tobago are that firstly, immediate death does not have a utility of zero (this is true regardless of whether linear time preferences are assumed, although the utility is closer to zero on assuming non-linear time preferences); secondly, that time preferences are non-linear; and thirdly, that when comparing the four DCE QALY tariffs with the cTTO tariff, assuming non-linear time preferences and anchoring on duration yields close agreement, while the other four choices yield poor agreement.

The non-linear time-preferences we observed have also been noted in a number of valuation studies using both DCE (18, 19, 28) and TTO (29-31), and a greater impact for DCE-based valuation over TTO-based valuation has been hypothesized (19). Mistakenly assuming linear time preferences led to a utility scale ranging from 0.338 to 1 when anchoring on immediate death, or to a range of -1.026 to 1 when anchoring on a duration of zero (with immediate death having an estimated utility of -2.1). The utility range on anchoring on immediate death, and the utility attached to immediate death are, in our opinion, unreasonable. Thus the assumption of linear time preferences is not only empirically refuted by the estimated discount parameter having a posterior distribution with most of its mass away from zero, it also leads to a value set that lacks face validity.

A shifting of preferences for immediate death away from zero on anchoring the tariff using duration has also been noted elsewhere. For example, immediate death was reported to have utilities of -0.46 (95% CI -0.79, -0.02) and -3.94 (-5.56, -2.36) in Australian studies of the EQ-5D-5L and SF-6D, respectively, on using the mixed logit model (11). Under a conditional logit model, anchoring on immediate death has been noted to lead to a shorter scale than anchoring on full health (32). Notably, however, these analyses all assumed linear time-preferences.

There are several explanations for the shift of immediate death away from zero. While equivalence to death has been formally defined (33), the processes by which respondents decide whether something is better or worse than dead do not always match this definition (34) and are, moreover, sensitive to framing (35).

Our results are specific to Trinidad and Tobago and do not necessarily generalize elsewhere.

When non-linear time preferences were accounted for and when anchoring was on duration, the observed utility range of -0.55 to 1 agreed well with that obtained for Trinidad & Tobago (24) using cTTO preferences elicited using the widely used EQ-VTv2 protocol (21) (utilities ranged from -0.6 to 1). Moreover, the two sets of preferences agreed well not just in range but at the individual state level (25).

In summary, we recommend that valuation studies using DCEs with duration design the choice tasks so as to be able estimate discount parameters, and examine whether non-linear time preferences are present. We further suggest that, given respondents' potential for heterogeneous interpretations of immediate death, tariffs be anchored on duration rather than immediate death.

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Appendix:

Model code linear model

```
model {
# N = number of respondents
# T = number of choice tasks per respondent
# A = number of alternatives per choice task
# V = number of explanatory variables (including non-linear time preference)

# likelihood
for (n in 1:N){
 for (t in 1:T){
  Y[n,t] <- 1
  Y[n,t] ~ dcat(prob[n, t, 1:2])
}}

# prob calculations <- user-written softmax function
for (n in 1:N){
 for (t in 1:T){
  prob[n,t,1:2] <- softmaxExpDeath(X[n,t,1,], Q[n,t,1], X[n,t,2,], Q[n,t,2], beta[n,], rate)
}}

# priors

# multivariate normal prior on beta
for (n in 1:N){ beta[n,1:V] ~ dmnorm(mu_beta[], prec_beta[,]) }
mu_beta[1:V] ~ dmnorm(hyper_mu_beta[],hyper_tau_beta[,])
prec_beta[1:V,1:V] ~ dwish(scaleMatrix[,],V)

for (b in 1:V){
```

```
 hyper_mu_beta[b] <- 0
 for (bb in 1:V){
   scaleMatrix[b,bb] <- equals(b,bb)
   hyper_tau_beta[b,bb] <- equals(b,bb)/100
}}

# normal prior on discount rate
rate <-0.0

# additional computations
# population SD
covar[1:V,1:V] <- inverse(prec_beta[,])
for (v in 1:V){ SD[v] <- sqrt(covar[v,v]) }

# log-likelihood
for (n in 1:N){
 for (t in 1:T) { LL_task[n,t] <- log( prob[n,t, Y[n,t] ]) }
 LL_resp[n] <- sum(LL_task[n,])
}
LL <- sum(LL_resp[])

# McFadden R-squared
LL_random <- N*T*log(0.5)
Rsq <- (LL - LL_random)/-LL_random

# QALY estimates (duration)
QALY_DUR[1] <- 1
for (v in 2:V){
  QALY_DUR[v] <- mu_beta[v] / mu_beta[1]
}
```

```
#worst possible health state 55555

worst[1] <- QALY_DUR[1] + QALY_DUR[5] + QALY_DUR[9] +QALY_DUR[13]
+QALY_DUR[17] + QALY_DUR[21]

# QALY estimates (immediate death)

QALY_DEAD[1] <- 1

for (v in 2:V-1){

  QALY_DEAD[v] <- QALY_DUR[v] *  (1/(1-QALY_DUR[V]) )

}

QALY_DEAD[V] <-0

worst[2] <- QALY_DEAD[1] + QALY_DEAD[5] + QALY_DEAD[9] +QALY_DEAD[13]
+QALY_DEAD[17] + QALY_DEAD[21]

}

}
```

Model code non-linear model

```
model {


# N = number of respondents

# T = number of choice tasks per respondent

# A = number of alternatives per choice task

# V = number of explanatory variables (including non-linear time preference)

# likelihood

for (n in 1:N){

 for (t in 1:T){

  Y[n,t] <- 1

  Y[n,t] ~ dcat(prob[n, t, 1:2])

}}


# prob calculations <- user-written softmax function

for (n in 1:N){
```

```
 for (t in 1:T){
  prob[n,t,1:2] <- softmaxExpDeath(X[n,t,1,], Q[n,t,1], X[n,t,2,], Q[n,t,2], beta[n,], rate)
}}

# priors

# multivariate normal prior on beta
for (n in 1:N){ beta[n,1:V] ~ dmnorm(mu_beta[], prec_beta[,]) }
mu_beta[1:V] ~ dmnorm(hyper_mu_beta[],hyper_tau_beta[,])
prec_beta[1:V,1:V] ~ dwish(scaleMatrix[,],V)

for (b in 1:V){
 hyper_mu_beta[b] <- 0
 for (bb in 1:V){
   scaleMatrix[b,bb] <- equals(b,bb)
   hyper_tau_beta[b,bb] <- equals(b,bb)/100
}}

# normal prior on discount rate
rate ~ dunif(0,1)

# additional computations
# population SD
covar[1:V,1:V] <- inverse(prec_beta[,])
for (v in 1:V){ SD[v] <- sqrt(covar[v,v]) }

# log-likelihood
for (n in 1:N){
 for (t in 1:T) { LL_task[n,t] <- log( prob[n,t, Y[n,t] ]) }
 LL_resp[n] <- sum(LL_task[n,])
```

```
}
LL <- sum(LL_resp[])

# McFadden R-squared
LL_random <- N*T*log(0.5)
Rsq <- (LL - LL_random)/-LL_random

# QALY estimates (duration)
QALY_DUR[1] <- 1
for (v in 2:V){
  QALY_DUR[v] <- mu_beta[v] / mu_beta[1]
}
#worst possible health state 55555
worst[1] <- QALY_DUR[1] + QALY_DUR[5] + QALY_DUR[9] +QALY_DUR[13]
+QALY_DUR[17] + QALY_DUR[21]

# QALY estimates (immediate death)
QALY_DEAD[1] <- 1
for (v in 2:V-1){
  QALY_DEAD[v] <- QALY_DUR[v] *  (1/(1-QALY_DUR[V]) )
}
QALY_DEAD[V] <-0
worst[2] <- QALY_DEAD[1] + QALY_DEAD[5] + QALY_DEAD[9] +QALY_DEAD[13]
+QALY_DEAD[17] + QALY_DEAD[21]
}
}
```