

ISPOR 7th Asia-Pacific Conference, Suntec Convention & Exhibition Center, Singapore Patient-Reported Outcomes & Patient Preference Research Issues Sunday, 4 September 2016, 3:45 PM - 4:45 PM @ Room 326

IP5: ESTIMATING COUNTRY-SPECIFIC EQ-5D-5L VALUE SETS USING A HYBRID REGRESSION MODEL: IS IT A GOOD IDEA FOR ASIA?

Moderator: Nan Luo National University of Singapore, Singapore Panelists: Mark Oppe, Juan M. Ramos-Goñi EuroQol Research Foundation, Rotterdam, The Netherlands Kim Rand-Hendriksen University of Oslo, Norway

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Background of the Issue





EQ-5D-5L

- A new version of the widely used EQ-5D instrument
- A preference-based instrument for measurement of healthrelated quality of life (HRQoL) consisting on:

- A descriptive system:

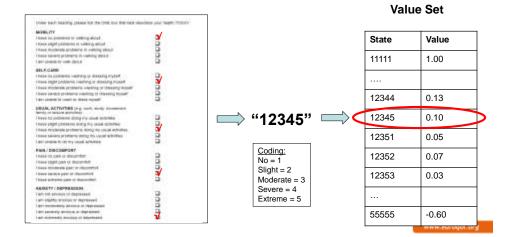
- 5 Dimensions: mobility, self-care, usual activities, pain/discomfort, anxiety/depression
- 5 Levels on each dimension: no, slight, moderate, severe, extreme
- Visual analogue scale (VAS)

- National value sets:

• Lists of values for each of the possible health state, on a cardinal scale anchored by 0 (death) and 1 (full health)



Deriving utility values using EQ-5D-5L





The EQ-5D-5L Valuation Study

- Target population general population
- Minimum sample size 1,000 individuals
- Data collection mode computer-assisted personal interviewing (CAPI)
- Valuation
 - Eliciting the value of 86 EQ-5D-5L health states using the time trade-off method (10 states per participant)
 - Eliciting the preferences for 196 DCE pairs of EQ-5D-5L health states (7 pairs per participants)
- Value set estimation
 - TTO data only
 - TTO and DCE data (the 'hybrid' model)



The 'Hybrid' model

Valuation and Modeling of EQ-5D-5L Health States Using a Hybrid Approach

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Background: The EQ-5D instrument is the most widely used prefemerce-based health-rolated quality of life quasisionnaire in cost-effectiveness analysis of health care technologies. Recently, a version called EQ-5D-5L with 5 levels on each dimension was developed. This manuscript explores the performance of a hybrid approach for the modeling of EQ-5D-5L valuation data.

Methods: Two elicitation techniques, the composite time made-off, and discrete choice experiments, were applied to a sample of the Spanish population (n=1000) using a compater-bused questionnain. The sampling process consisted of 2 stages stratified sampling of geographic area, followed by systematic sampling in rach area. A hybrid regression model combining composite time made-off and discrete choice data was used to estimate the potential value sets using main effects as starting point. The comperison between the models was performed using the enterin of logical consistency, goodness of fit, and parsimony.

Results: Twenty-seven participants from the 1000 were removed following the exclusion criteria. The best-fitted model included 2 significant interaction terms but resulted in marginal improvements in model in compared to the main effects model. We therefore selected the model results with main effects as a potential value set for this methodological study, based on the paraimony enterna. The results showed that the main effects hybrid model was consistent, with a marge of ultimy values between 1 and ~0.224.

Conclusion: This paper shows the feasibility of using a hybrid approach to estimate a value set for EQ-5D-5L valuation data.

Key Words: utility theory, quality of life, maximum likelihood estimation, time trade-off, discrete choice experiment

(Med Care 2014;00: 000-000)

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Published country-specific EQ-5D-5L value sets

Country	TTO data only	TTO + DCE (the 'hybrid' model)
England		$\sqrt{*}$
Spain		√**
The Netherlands	\checkmark	
Uruguay	\checkmark	
Japan	\checkmark	
South Korea	\checkmark	

*The working OHE paper is online but the Journal paper is still under review

**Spanish team published a methodological test of the hybrid approach while the value set has not been published yet

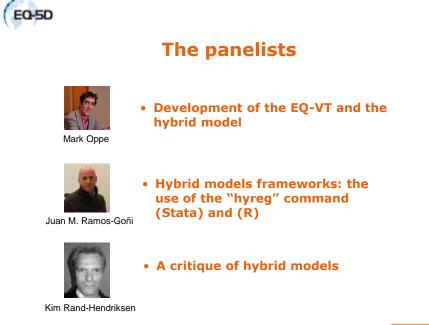




The issue

- Shall we adopt the 'hybrid' model to estimate EQ-5D-5L value sets in Asia?
 - What is better as valuation technique: TTO or DCE?
 - How can TTO and DCE data be combined to predict EQ-5D-5L health states?
 - Is 'hybrid' a better approach than the TTO only approach?

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Development of the EQ-VT and the hybrid model



Mark Oppe, PhD EuroQol Research Foundation

Singapore, September 2016



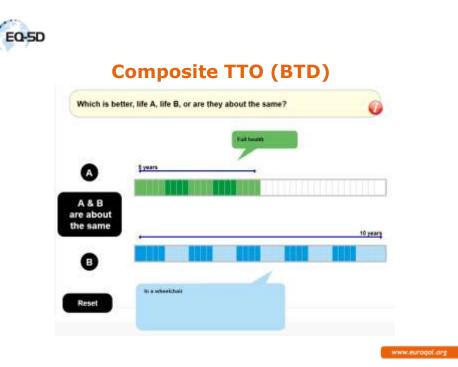
- Early valuation research on EQ-5D used VAS
- The UK MVH study first to use the TTO
- Became the 'default' protocol used in other countries
- Somewhat inconsistent approaches between countries limited comparability





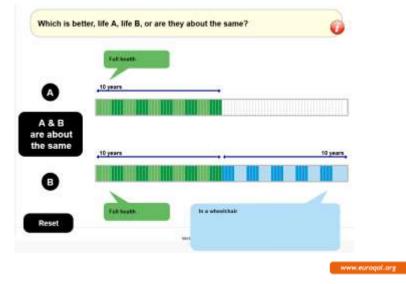
Development of the EQ-VT

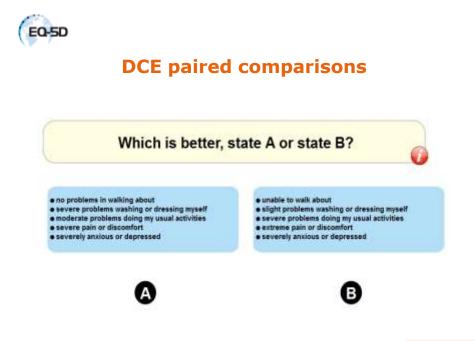
- Why a new valuation protocol?
 - Develop better valuation methods for valuing EQ-5D-5L
 - Take advantage of advances in computer-based methods
 - Provide a fully documented, evidence-based protocol to be used in all countries – ensure consistency
- 10 multinational pilot studies
 - Different modes of administration
 - Different types of TTO
 - Different secondary tasks (VAS, DCE, BWS)





Composite TTO (WTD)







Experimental Design

DESIGN SPECIFICATIONS	сТТО	DCE
N respondents	1000	1000
N blocks	10	28
N states/pairs	80 + 6 fixed	186 + 10 fixed very mild
N states/pairs per resp	10	7
N obs per state/pair	100 (for the set of 80 states)	36
Optimisation Algorithm	Monte Carlo simulation	Bayesian efficient design

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Tasks included in EQ-VT version 2.0

- Self reported health on the EQ-5D-5L descriptive system
- Self reported health on the EQ-VAS
- Background questions

Composite Time Trade-Off

- Instructions and example of TTO task, 3 practice states
- TTO valuation of 10 EQ-5D-5L states
- TTO debriefing/structured feedback
- TTO feedback module

Discrete Choice

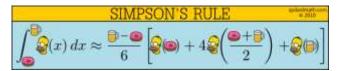
- Instructions of DC task
- DC valuation of 7 pairs of EQ-5D-5L states
- DC debriefing/structured feedback

Cyclic quality control process



Modelling TTO and DCE

• Individuals have a utility function which determines their preferences over health states



- TTO & DCE methods both try to measure the same utility function
- TTO & DCE each have their own weaknesses
 - e.g. scale compatibility (BTD vs WTD) for C-TTO
 - e.g. no anchors for use in QALY calculations for DCE
- Which method should we choose?

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TTO, DCE or both?

- TTO: trade-off between quality of life and length of life
 How many years are you willing to give up to avoid being in impaired health?
- DCE: trade-off between quality of life and quality of life - Which health state is better?
- Both questions provide relevant information
- View TTO and DCE as complementary sources of information instead of competing

Include both types of information in a single hybrid model



Log likelihood of basic hybrid model (OLS & clogit)

$$lnL = -\frac{1}{2} * \sum_{j \in C} \left\{ ln(2\pi\sigma^2) + \left(\frac{y_j - x\beta}{\sigma}\right)^2 \right\}$$
$$+ \sum_{j \in D} \left\{ ln \left(\frac{1}{1 + e^{(-x\beta')}}\right) * y_j + ln \left(\frac{e^{(-x\beta')}}{1 + e^{(-x\beta')}}\right) * (1 - y_j) \right\}$$

proportional rescaling parameter $\theta,$ such that $\beta' = \beta * \theta$

EQ-5D Apples & Oranges or a Fruit Salad?

- Hybrid:
 - Uses all available information
 - Hybrid estimates are typically between estimates of TTO alone and estimates of DCE
 - DCE can help mitigate issues present in TTO and v.v.
- Since the "true" utilities are not known, ultimately the choice is a normative one:
 - Which (imperfect) utility theory?
 - Which (imperfect) data collection technique?
- Pragmatic basis for choice: data quality; value range; performance in applications



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Hybrid models frameworks The use the "hyreg" command (Stata)



Juan M. Ramos-Goñi, MSc EuroQol Research Foundation

Singapore, September 2016

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History of modelling approaches

- EQ-5D-5L valuation studies were first launched in 2012, with Spain, UK, The Netherlands, Canada and China being the first countries to test EQ-VT
- The first test of the hybrid model using 5L valuation data was done using Spanish data
- The test indicates that the approach is feasible, but having some limitations





Programing the hybrid model

- First implementation was made in R by Ben van Hout (not user friendly code)
- In parallel a Stata implementation was made by Juan M. Ramos-Goñi (not user friendly code)
- Improvements were started in parallel:
 - Random coefficients for TTO data (Ben van Hout)
 - Inclusion of interval data for TTO data (Benjamin Craig and Juan M. Ramos-Goñi)
 - Censoring TTO observations (Ben van Hout)
 - Including the mix with a conditional probit instead of logit (Benjamin Craig and Juan M. Ramos-Goñi)
- At the end it was decided to integrate as much features as possible in "user friendly commands" for Stata and R.



The Stata "hyreg" command

• Syntax

hyreg depvar1 [depvar2] [indepvars] [if] [in] ,
datatype(varname)
[interval
contdist(normal | logistic)
dichdist(normal | logistic)
II(#) ul(#)
hetcont(varlist) hetdich(varlist)
noconstant
vce(oim | opg | robust | cluster varname) maximize options]





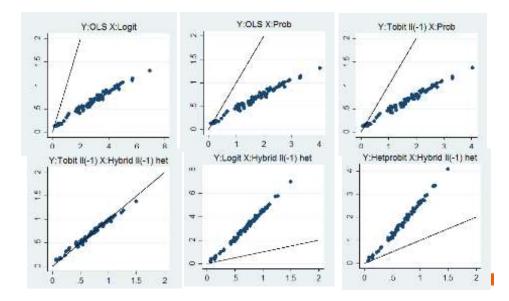
"hyreg output"

$$lnL = -\frac{1}{2} * \sum_{j \in C} \left\{ \ln(2\pi\sigma^2) + \left(\frac{y_j - x\beta}{\sigma}\right)^2 \right\}$$
$$+ \sum_{j \in D} \left\{ ln \left(\frac{1}{1 + e^{(-x\beta*\theta)}}\right) * y_j + ln \left(\frac{e^{(-x\beta*\theta)}}{1 + e^{(-x\beta*\theta)}}\right) * (1 - y_j) \right\}$$

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Summary

- The hybrid approach is feasible
- DCE predictions and TTO predictions are highly correlated
- High concordance between TTO models and hybrid models
- High correlation between DCE models and hybrid models
- The estimated coefficient from hybrid model are more precise than (<S.t error) than the ones from DCE or TTO models

•Why shouldn't it be done?



A critique of hybrid models



Kim Rand-Hendriksen, PhD University of Oslo

Singapore, September 2016





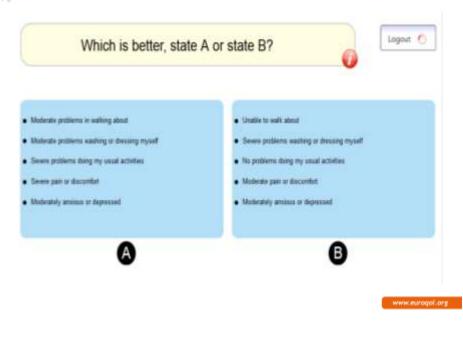
Battle plan

- 1. Conceptual issues
 - The relationship between utilities and DCE
 - What we know, and what we don't know
 - Lack of obvious counterfactual
- 2. Practical issues
 - Shared constant term/intercept between DCE and TTO
 - "Flat" areas when combining two data types with different maxima
 - Weights
 - Problems with the handling of differences between the TTO and DCE functions
- 3. Conclusion

EQ-5D The relationship between utilities and DCE (RUT)

- DCE/TTO hybrid models rest on the assumption that DCE and TTO are equally valid, or that it is unknown which is more valid
- TTO measures strength of preference directly, on and individual level. Population aggregates of this will therefore take into account variation in strength of preference.
- DCE, when applied to a population, as opposed to repeated measures of an individual, does not (necessarily) take into account variation in individual strength of preference.
- Choices for health states could reflect differences in "taste" for health
 - Consider a choice between chocolate and caramel ice cream. If it is observed that 60% prefer chocolate, we cannot directly infer that chocolate has a higher value than caramel, since the minority preferring caramel could display a substantially greater willingness to pay than the proponents of chocolate. TTO catches this difference (at least in theory), while DCE does not.
 - This is a general critique of DCEs for health state valuation, and does not apply only to hybrids.







Lack of obvious counterfactual

- With mean-based modeling of TTO, predictions can be directly compared to observed means. This allows leave-out cross-validation with a true counterfactual for comparison.
- For "pure" DCE models, predictions can be compared to observed choice probabilities.
- With hybrid models, performance cannot be easily measured by these kinds of comparison.
- For more complex hybrids (i.e. predicting intervals, handling censoring, heteroscedastic standard deviations, models for the link between TTO and DCE...), determining model validity becomes very tricky.
- Likelihood-based comparison remains possible, but are uninformative as to the validity of the assumptions behind the likelihood function.



Practical issues Shared intercept/constant term

- 1. hyreg value _mo2-_ad5, datatype(_method) nocons
- hyreg value _mo2-_ad5, datatype(_method)
- Code 1 fits a model with 20 parameters to both TTO and DCE data, with no constant term/intercept
- Code 2 fits the same model, adding a constant term. All parameters, including the constant term shared, meaning that they are fitted to both TTO and DCE observations.
- Unfortunately, the constant term does not mean the same for the two kinds of data, and the sign of the constant for DCE is arbitrary. I will illustrate with an example.

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Constant problems

- Data from the DHS (demographic and health surveys) run by USAID
- Age, sex, height, and weight for approx. 3000 children aged 0-5 years
- Linear regression model to predict height based on age (dummies for 1, 2, 3, and 4 years) and sex (dummy for girl)

h = INTERCEPT + S + A1 + A2 + A3 + A4Paraneters: Estimate Std., Error STGMA 18.154619 8.1839315 INTERCEPT 64.086948 0.6976458 -1.389705 0.5211695 \$ 14.798526 8.9816843 1.1 A2 8.354346 0.8481761 8.964731 8.8817649 A3 7.344159 8.7644284 44

Intercept is interpretable as estimated average height for boys at <1 years.



Constant problems cont'd

- Generate 10 000 "DCE"s, by random sampling (with replacement)
- Target variable 1 if left child is tallest. Ties removed. Conditional logit model: P.

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	Estimate	StdError
INTERCEPT	-0.003116987	0.01568021
5	-0.097730655	0.02234994
A1	1.004000093	0.04862737
A2	0.629414872	0.03525029
A3	0.573683424	0.03238180
A4	0.528308318	0.03269077

• Here, the intercept is the average right/left bias, which is negligible due to the random sampling.



Now as a hybrid

• OLS for continuous, conditional logit for generated "DCE"

Parameters:

Estimate	Std. Error
25.976282	0.5459067
38.619536	0.8219985
7.743260	0,5916663
2.191158	0.7061509
51.815555	1.1331342
19.021508	1,1487489
18.434260	1.0577370
15.985168	1.8498862
	25.976202 38.619536 7.743260 2.191158 51.815555 19.021508 18.434260

- Now, the intercept has no direct interpretation.
- The model also fits quite badly:

	Alone	Hybrid
Loglik for continuous:	-5695,9	-7126,4
Loglik for "DCE" :	-4176,7	-4340,6



Hybrid with separate intercepts

• INTERCEPT for continuous, INTERCEPT_DCE for "DCE"

	Estimate	StdError
SIGMA	10.15649782	0.1839824
INTERCEPT_TTO	64.11278521	8.5847958
INTERCEPT_DCF	-8.84476864	8.2262171
THETA	14.42715917	8.3858576
S	-1.40353266	0.2748719
A1	14.57344660	8.5649897
AZ	8.89915133	8.4536258
A3	8.44354327	8.4271581
44	7.54903476	8.4188864

	Alone	Hybrid1 Hybrid2
Loglik for continuous:	-5695,9	-7126,4 -5695,3
Loglik for "DCE" :	-4176,7	-4340,6 -4176,8



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Right/left bias

"Original"			Reversed			
	Estimate	Std. Error	Sec. 1997	Estinate	Std. Error	
(Intercept)	0.21164586	0.0266645	(Intercept)	-8.21164586	0.0266645	
incr_mo2_diff	0.44230775	0.0526517	incr mo2 diff	0.44230775	0.0526517	
incr mo3 diff	-0.00271160	0.0602873	incr mo3 diff	-0.00271160	0.0602873	
incr mod diff	8,77762394	0.0592446	incr mod diff	0.77762394	0.0592446	
incr_mo5_diff	1.16562366	0.0653388	incr mos diff	1.16562366	0.0653388	
incr_sc2_diff	0.35921265	0.0576461	incr sc2 diff	0.35921265	0.0576461	
incr_sc3_diff	-0.00847601	0.0625683	incr sc3 diff	-0.00847601	0.0625683	
incr_sc4_diff	0.67629896	8.8661428	incr sc4 diff	0.67629896	0.0661428	
incr_sc5_diff	0.39924359	0.0615881	incr sc5 diff	8.39924359	0,0615881	
incr_ua2_diff	8.27154495	0.8549798	incr uaz diff	0.27154495	0.0549798	
incr_ua3_diff	0,04449129	0.8615065	incr was diff	0.04449129	0.0615065	
incr us4 diff	0.53745959	0.0619102	incr us4 diff	0.53745959	0.0619102	
incr_ua5_diff	0.57164557	0.0636063	incr ua5 diff	8.57164557	0.0636863	
incr pd2 diff	0.25449076	0.0580883	incr pd2 diff	0.25449076	0.0580883	
incr_pd3_diff	8.83962988	0.0633029	incr pd3 diff	8.03962980	0.0633829	
incr_pd4_diff	0.80788425	0.0642941	incr pd4 diff	0.80788425	0.0642941	
incr_pd5_diff	0.30395110	0.0638620	incr pd5 diff	0.30395110	0.0638620	
incr_ad2_diff	0.27174584	0.0603230	incr ad2 diff	0.27174584	0.0603230	
incr_ad3_diff	0.19483877	8.8615435	incr ad3 diff	8.19483877	0.0615435	
incr_ad4_diff	0.88367616	0.0655376	incr ad4 diff	0.88367616	0.0655376	
incr ad5 diff	0.52791784	0.8654448	incr ads diff	0.52791784	0.0654440	



Right/left bias with hybrids and shared intercept

• Sign of DCE influences joint intercept, and model fit

A - B		В	- A		
Estimate StdError		Estimate StdError			
THETA	47.51251	1.0218045	THETA	52.772017	1.1346890
INTERCEPT	19.70110	0.6816674	INTERCEPT	2.155600	0.7820390
5	2.68336	0.7147274	5	4.221512	0.8438539
A1	43.69928	1.1060360	A1	54,971610	1.3074188
A2	17,45344	1.1748502	A2	19.586300	1.3842987
A3	17.21160	1.1099331	A3	19.516540	1.3860186
A4	13.35570	1.0740309	A4	14.812707	1.2673559
SIGMA	21.36575	8.4746664	SIGNA	27.772534	0.6207201
D	CE CONT	INUCUS		DCE CON	TINUOUS
-4946.7	-68	28.629	-4985.	983 -7	228.311

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Removing the intercept

• No impact from arbitrary choice of A and B, but (in some cases) bad model fit

Parameters:

	Estimate	StdError
THETA	52.669965	1.1332921
5	4,333265	0.8536047
A1	56.244804	1.2443716
AZ	19.891977	1.3961106
A3	19.795430	1.3172189
A4	15.023894	1.2801413
SIGMA	28.611836	0.5587462

DCE CONTINUOUS -4944.324 -7273.685





Separate intercepts

• With separate intercepts, model fit is improved

A - B		B - A				
	Estimate StdError		Estimate StdError			
THETA	18.309488	0.4926709	THETA	18,389480	8.4926709	
INTERCEPT_DC	E 3.849551	0.2821264	INTERCEPT_DC	E -3.849551	0.2821254	
5	-1.471070	0.3185478	5	-1.471070	0.3105478	
A1	13.487485	0.5971305	A1	13.487405	0.5971305	
A.2	9.250974	0.5088136	A2	9.250974	0.5088136	
A3	8,999988	0.4824521	A3	8,999900	8.4824521	
A4	7.280235	0.4662980	A4	7.280235	8.4662980	
SIGNA	10.162608	0.1841837	SIGMA	18.162608	0.1841837	
INTERCEPT	64.634485	0.5934544	INTERCEPT	64.634485	8.5934544	
DCE	CONTINUOUS	sum	DCE	CONTINUOUS	Sut	
-4735.784	-5696.184	-10431.968	-4735.784	-5695.184	-18431.968	

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"Flat" areas when combining two data types with different maxima

- Since the hybrid maximizes the sum of TTO and DCE loglikelihood, and the two are often different, parameter changes that improve TTO fit can often reduce DCE fit, and vice versa
- This results in ranges of parameter values for which the sum of log-likelihoods changes very little "flat" areas. Such flat areas make the model unstable, in that quite small changes can result in relatively large changes in the resulting fitted model.





Weights

- Maximum likelihood is a sum of likelihoods for each prediction over each observation. Increasing the number of observations increases the maximum likelihood.
- When maximizing the sum of two different sums of likelihoods, the relative weight of one type of data over the other will be a function of how many observations are present of each.
- The fitting function is not sensitive to the absolute magnitude of likelihoods, but to the magnitude of the change from small changes in the parameters.
- If a change of one unit for a parameter results in a positive change of 1.1 for the sum likelihood for TTO, and -1 for DCE, a >10% increase in the number of DCE observations will reverse the direction of change to the fitted model.

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Conclusions

- TTO and DCE are different
- We know more about the problems with TTO than with DCE
- We might not be combining two measures of the same, but two measures of different things
- Various practical issues that have not been adequately addressed yet
- Are hybrids interesting? Yes.
- Are we at the point where we should replace TTO-only models with TTO/DCE-hybrids?

My personal opinion is that this is premature.





Brief Responses from Juan M. Ramos-Goñi & Mark Oppe



Open Discussion

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