Maximise your utility by minimising regret: contrasts between two behavioural paradigms

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Presentation outline

RUM

- Random utility maximisation has been the key paradigm in modelling individual decisions for four decades
- Idea is that decision makers quantify the appeal of an alternative as a utility and choose the alternative which maximises their utility or minimises their disutility
- An inherent characteristic of this framework is the notion of trading between attributes, with poor performance on one attribute (e.g. cost) being compensated for by good performance on another attribute (e.g. time)

Alternatives to RUM

- RUM is in very widespread use, with a range of different models, going way beyond MNL in terms of complexity
- However, RUM has always been criticised, especially by behaviour economists and mathematical psychologists, as giving a simplified representation of reality
- Various alternative models exist, for example elimination by aspects, but these structures have disadvantages in application to large scale problems with large numbers of attributes and alternatives, and also in terms of producing outputs that can be used in economic analysis
- Most recently, there has been growing interest in modelling regret as an alternative to utility

RRM I

- Regret is a negative emotion experienced when we imagine that a present situation would have been better if we had made a different decision
- Several adaptations are needed to allow regret models to be estimated with the typical, multi-alternative, multi-attribute data obtained in choice experiments
- Initial work by by Chorus et *al*. defines a Random Regret Minimisation (RRM) model where regret is equal to the largest among the binary regrets based on pairwise comparisons of the considered (i) and remaining alternatives ($i \neq j$)

RRM II

- In this specification, regret is computed only considering the best forgone alternative

$$R_{i,n,t} = max_{i \neq j} \left\{ \sum_{k=1..K} max \left\{ 0, \beta_k (x_{j,k,n,t} - x_{i,k,n,t}) \right\} \right\}$$

- Choice probability for alternative *i* with *iid* type 1 extreme value errors is written $P_{i,n,t} = \frac{exp(-R_{i,n,t})}{\sum exp(-R_{j,n,t})}$

RRM III

- RRM model was later revised to move away from just comparison with the best foregone alternative on each attribute
- Incorporate comparisons across all pairs of alternatives

$$R_{i,n,t} = \sum_{j \neq i} \sum_{k=1..K} \ln\left(1 + e^{\beta_k\left(x_{j,k,n,t} - x_{i,k,n,t}\right)}\right)$$

Contrasts I

- Recent work by Chorus and colleagues in this context also shows some evidence that on some datasets, RRM works better than RUM, with the opposite being the case on other datasets
- Also some insights by allowing jointly for the two paradigms within a single model
- The two models are inherently different in terms of interpretation
- Whereas a RUM based analysis derives the sensitivity to attributes, RRM estimates the potential contribution to regret feelings of each attribute.
- Due to this, the comparison across models is not straightforward

Contrasts II

- RRM seems to often favour compromise alternatives, i.e. it is a suitable mechanism for a choice situation where the decision maker wants to avoid poor performance on one or more attributes
- Behaviourally, this could make a lot of sense especially in choices of (long term) products as opposed to (short term) services
- Thus far, it is not possible to easily use RRM for welfare analysis, e.g. computing WTP measures
- Questionable whether this is possible at all given the way regret depends also on performance of other alternatives
- However, it is likely to be a very suitable approach in forecasting scenarios, and can be estimated with standard MNL software

Introduction

- Much of the findings in terms of empirical comparisons shows small differences in fit and no particular patterns
- Our focus of attention is the presence of a status quo, do nothing, no choice or opt out alternative
- Sometimes specified to designate none of the alternatives as ones the respondent would choose, others as a no opinion, or a position of indifference between the competing attributes
- The specific choice of approach used in surveys is seemingly arbitrary, with little or no consideration as to the impact on behaviour and appropriate modelling approach
- Our argument is that the way in which the opt out option is framed to participants plays an important role in which modelling approach is appropriate for the resulting data

Theory I

- RRM postulates that the regret associated with an alternative depends on the performance of competing alternatives
- RUM postulates that the utility of an alternative solely depends on that alternative's characteristics
- We expect a RRM model to do poorly - compared to RUM - when the opt out option is framed as a 'none of these' option
    - RRM constant does not match the meaning of 'none of these'
    - High values imply that the expected regret of choosing from the choice alternatives is so high that opting out is preferred
    - However, expected regret of choosing from choice alternatives says something about the relative performance of alternatives, and nothing about the absolute quality of the alternatives in that set
    - Regret exists by the virtue of comparisons, and improving the performance of all alternatives to a similar extent does not change regrets

Theory II

- Example of stated route choice experiment
- Choice set 1 contains three alternative routes (A, B, and C) between an origin and destination
- Route A's travel time equals 40 minutes, that of B equals 45 minutes, and that of C equals 50 minutes. Travel costs are 5 euros for A, 2.5 for B and 0 for C
- Now suppose that in choice set 2, the travel times of all three routes are increased by 30 minutes, while costs are increased by 2.5 euros for all routes
- Clearly, one expects many more people choosing the 'no travel' opt out
- However, it is easily seen that the regrets associated with the alternatives are the same in both choice sets, given that the attribute differences across alternatives remain the same
- Expect RRM to perform poorly

Theory III

- Expect a RUM model to do poorly when the opt out option is framed as an 'I am indifferent' option
- High values of constant imply that the expected utility of choosing from the set of choice alternatives is so low that opting out is preferred
- Expected utility of choosing from a set of alternatives says something about the absolute performance of alternatives in the set, and nothing about the relative quality
- When the opt out-option in an experiment is framed in a way ('I am indifferent'), i.e., there is no clear winner, this framing in terms of relative quality of the alternatives provides a mismatch with the meaning of a constant in a RUM model

Theory IV

- Return to the empirical example from before but assume that opt out is framed as 'I am indifferent'
- One expects no differences between choice situations 1 and 2 in terms of the number of people choosing the opt out option for reasons of being indifferent between the three routes
- However, the utilities associated with the alternatives are of course very different in choice sets 1 and 2
- For the RUM model, choice sets 1 and 2 are very different, whereas a participant in both sets is equally likely to be indifferent between choice options
- Expect RUM to perform poorly

Data I

- Stated choice data relating to willingness to pay for an advanced Public Transport information service
- Four attributes were used to describe the alternatives in the choice task:
    - Type of information provided by the service (times; times and search for routes; times and advice on best route)
    - Who has to take the initiative to provide/acquire the information (traveller; service; both)
    - Reliability of the information (expressed in minutes)
    - Cost
- Included a ’none of these’ alternative as the opt out
- Estimated models with and without the opt out
- All models (also for second case study) include error components to capture repeated choice nature of the data

Results I

	Opt Out Excluded				"None of These" Included			
	RUM		RRM		RUM		RRM	
	Parameter Estimates (*t*-ratio)							
Times & Search	0.2384	(2.2)	0.1713	(2.38)	0.1881	(1.61)	0.0986	(1.39)
Times & Advice	0.6961	(6.19)	0.448	(5.99)	0.6625	(5.51)	0.3914	(5.66)
Info-Initiative	0.0195	(0.18)	0.0366	(0.5)	-0.0206	(-0.18)	-0.1038	(-1.57)
Both-Initiative	0.228	(2.2)	0.1736	(2.54)	0.2342	(2.19)	0.1048	(1.65)
Unreliability	-0.0772	(-3.48)	-0.0532	(-3.58)	-0.1019	(-4.26)	-0.0679	(-4.43)
Cost	-0.9407	(-17.24)	-0.6565	(-15.85)	-1.0893	(-17.73)	-0.7081	(-15.6)
"None of These"	---	---	---	---	-1.7297	(-9.5)	-8.6616	(-74.48)
σ	0.3474	(3.96)	0.3269	(3.62)	0.9226	(12.25)	0.7714	(10.96)
	Model Fit Statistics							
Observations	1,463		1,463		1,836		1,836	
Log-Likelihood	-1,171.42		-1,174.22		-1,894.68		-2,015.90	
adj. ρ^2	0.2668		0.2651		0.2525		0.2048	
	Parameter/Cost Ratio							
Times & Search	-0.253		-0.261		-0.173		-0.139	
Times & Advice	-0.740		-0.682		-0.608		-0.553	
Info-Initiative	-0.021		-0.056		0.019		0.147	
Both-Initiative	-0.242		-0.265		-0.215		-0.148	
Unreliability	0.082		0.081		0.094		0.096	

Data II

- Examination of salary and travel time trade-offs in the Stockholm region of Sweden
- Two different scenarios were administered
  - first required respondents to consider the hypothetical scenario that their workplace would be moved to a location that would imply a longer commuting time and that this disutility would be compensated by a higher monthly net wage
  - second experiment looks jointly at the times and salaries for both members of the household
- Common across both games was the presentation of two competing alternatives along with a third 'Indifferent' option
- Estimated models with and without the opt out

Results II, game 1

	Opt Out Excluded				"Indifferent" Included			
	RUM		RRM		RUM		RRM	
	Parameter Estimates (*t*-ratio)							
Own travel time	-0.3229	(-27.3)	-0.3229	(-27.3)	-0.0734	(-26.35)	-0.2561	(-37.79)
Own salary	4.2960	(23.53)	4.2960	(23.53)	0.0118	(1.57)	3.1143	(30.06)
"Indifferent"	---	---	---	---	-5.4905	(-20.9)	-6.2509	(-41.52)
σ	1.7335	(20.3)	1.7335	(20.3)	1.2043	(18.02)	1.4565	(23.89)
	Model Fit Statistics							
Observations	8,929		8,929		9,432		9,432	
Log-Likelihood	-3,404.93		-3,404.93		-6,608.48		-5,371.62	
adj. ρ^2	0.4787		0.4787		0.3620		0.4813	
	Parameter/Cost Ratio							
Own travel time	-0.075		-0.075		-6.239		-0.082	

Results II, game 2

	Opt Out Excluded				"Indifferent" Included			
	RUM		RRM		RUM		RRM	
	Parameter Estimates (t-ratio)							
Own travel time	-0.2516	(-24.05)	-0.2516	(-24.05)	-0.0636	(-17.89)	-0.2367	(-27)
Own salary	3.6491	(21.11)	3.6491	(21.11)	0.0177	(1.67)	3.1509	(23.19)
Partner's travel time	-0.2455	(-26.87)	-0.2455	(-26.87)	-0.0663	(-16.94)	-0.2315	(-28.89)
Partner's salary	3.0330	(16.34)	3.0330	(16.34)	0.0126	(1.26)	2.8481	(17.47)
"Indifferent"	---	---	---	---	-7.7962	(-15.87)	-9.4107	(-39.84)
σ	2.0072	(22.45)	2.0072	(22.45)	2.1269	(19.36)	2.1592	(25.82)
	Model Fit Statistics							
Observations	10,064		10,064		10,609		10,609	
Log-Likelihood	-3,694.57		-3,694.57		-6,539.03		-5,409.53	
adj. ρ^2	0.4969		0.4969		0.4384		0.5354	
	Parameter/Cost Ratio							
Own travel time	-0.069		-0.069		-3.599		-0.075	
Partner's travel time	-0.081		-0.081		-5.265		-0.081	

Conclusions

- Empirical results support our hypothesis that RRM does worse than RUM when the opt out option is framed as a 'none of these' option, but that RRM does better than RUM when the opt out option is framed as a 'too close to call' or 'indifferent' option
- Argument is based on the contrast between a situation where all alternatives are rejected by a respondent and a situation where the alternatives are too similar to one another to make a meaningful choice
- Suggests that analysts need to take care in how to specify opt outs in their surveys as it may determine a priori which model is suitable for their data
- 'Wrong' model leads to much lower fit and bias in parameters

Introduction

- Haven't really looked at what might drive the choice of an appropriate decision rule at the level of a person
- Can allow for different rules for different people in a sample
- Can explain, especially in SP, how this relates to their real world situation

Methodology I

- In line with work by Hess et al. (2012), a general specification of a model allowing for different decision rules within a latent class framework is given by:

$$LC_n\left(\beta_1,\ldots,\beta_S,\pi_1,\ldots,\pi_S\right)=\sum_{s=1}^{S}\pi_s LC_{n,s}\left(\beta_s\right)$$

  where LC_n is the contribution to the likelihood function of the observed choices for respondent n (out of N)

- Two key shortcomings:
  - Risk of confounding between heterogeneity in sensitivities and heterogeneity in decision rules
  - Limited insight into the factors determining the choice of decision rule

Methodology II

- Hess et al. (2012) deal with confounding by including additional random heterogeneity in a continuous manner, i.e. $\beta_s \sim f(\beta_s \mid \Omega_s)$:

$$LC_n(\Omega_1, \ldots, \Omega_S, \pi_1, \ldots, \pi_S) = \sum_{s=1}^{S} \pi_s \left[\int_{\beta_s} LC_{n,s}(\beta_s) f(\beta_s \mid \Omega_s)\, \mathrm{d}\beta_s \right],$$

- Imposes substantial demands in terms of computational complexity as well as empirical identification
- We put forward the use of an additional layer of latent classes:

$$LC_n\left(\beta^{(1)}, \ldots, \beta^{(S)}, \pi, \varpi^{(1)}, \ldots, \varpi^{(S)}\right) = \sum_{s=1}^{S} \pi_s \sum_{k=1}^{K_s} \varpi_{k,s} LC_{n,s}(\beta_{s,k})$$

- Model now uses K_s different classes for model s
- Averaging across classes is performed at the level of individual respondents, recognising the repeated choice nature of the data

Methodology III

- Other shortcoming is the lack of explanation as to what drives the likelihood of a given paradigm being more appropriate for one specific respondent than another
- Rather than linking class allocation probabilities π to respondent specific characteristics, we link it to unobserved character traits
- Working with a single such trait for the sake of exposition, let us refer to it as α_n for respondent n
- Simplifying our overall structure further to the case of just two decision paradigms, we now write:

$$\pi_{n,1} = \frac{1}{1 + e^{\delta_{\pi,2} + \tau\alpha_n}} \tag{1}$$

$$\pi_{n,2} = \frac{e^{\delta_{\pi,2} + \tau\alpha_n}}{1 + e^{\delta_{\pi,2} + \tau\alpha_n}}. \tag{2}$$

where α_n is a latent component specific to respondent n

Methodology IV

- Model the value of α_n as:

$$\alpha_n = \sum_{l=1}^{L} h_l\left(z_{n,l}, \gamma_l\right) + \eta_n$$

  where η_n is standard Normal across individuals

- Likely difficult to find meaningful socio-demographic explanators for underlying character traits
- More likely to be intrinsic to a person and shaped by experience and lifestyle, either of which are difficult to capture in data

Methodology V

- Thus far, simply allows for random (through η_n) and deterministic (through $\gamma' z_n$) variations in the class allocation probabilities
- Estimates relationship between latent character traits and likely decision rules only on the basis of data on choices
- Only provide a snapshot of preferences in a very controlled settings at a particular point in time
- Arguably do not permit us to make the full link to what we regard as person specific character traits which are constant over a longer time horizon
- Make use of additional information relating to other manifestations of these character traits

Methodology VI

- Assume data contains additional variables which we hypothesise to be a function of the same latent character traits
- Identification of such variables is a difficult task and could encompass a range of different formats, be it answers to questions on attitudes and perceptions, or descriptors of lifestyle and past experiences
- Of crucial importance within the behavioural concept at the heart of our approach is that they need to relate to long term traits rather than short term feelings
- Model values of these *indicators*, say $I_{n,1}$ to $I_{n,M}$ grouped together into a vector I_n as:

$$I_{n,m} = \delta_{I,m} + \zeta_m \alpha_n + \upsilon_{n,m}$$

- i.e. they are linked to the same underlying character traits α_n

Methodology VI

- In estimation, we now jointly maximise the likelihood of the observed choices and the observed values of the indicators
- Enable the model to create a link between the behaviour in the short term context (i.e. stated choice) and the longer term character traits
- First hybrid model allowing long term character traits to explain decision rule heterogeneity in choice data

$$L_n = \int_{\eta_n} \left[\sum_{s=1}^{S} \pi_{n,s}(\alpha_n) \sum_{k=1}^{K_s} \varpi_{n,s,k} LC_{n,s}(\beta_{s,k}) \right] \left[\prod_{m=1}^{M} LI_{n,m}(\alpha_n) \right] \phi(\eta_n)\, \mathrm{d}\eta_n$$

Data I

- Online survey conducted on rail and bus commuters in the UK in 2010
- Route choice between reference trip and two hypothetical alternatives, with six attributes (travel time, fare, rate of crowded trips, rate of delays, average length of delays, provision of a delay information service)
- Collected data concerning acceptable and ideal conditions for each attribute of their reference trip
- Hypothesis is that a declared shortfall from ideal reference values makes it less likely that the respondent chose that real world commute trip by minimising regret
- Hypothesise that travellers have a certain amount of influence on their commute journey and over time align it with their aspirations
- Test whether the size of the gap between ideal or acceptable and current values is related to the predisposition to use a regret-minimising decision rule

Utility specification

- Make use of two paradigm specific latent classes to capture additional heterogeneity, such that $K_s = 2, \forall s$
- The deterministic utility for alternative i ($i = 1, \ldots, 3$) for respondent n in choice task t is given:

$$\begin{aligned} V_{n,t,i,k} = & \ \delta_{RUM,i,k} \\ & + \beta_{RUM,TT,k} TT_{n,t,i} \\ & + \beta_{RUM,LF,k} \ln\left(FARE_{n,t,i}\right) \\ & + \beta_{RUM,RA,k} RA_{n,t,i} \\ & + \beta_{RUM,RI,k} RI_{n,t,i} \\ & + \beta_{RUM,C,k} C_{n,t,i} \end{aligned}$$

Regret specification

- The deterministic regret for alternative i ($i = 1, \ldots, 3$) for respondent n in choice task t is given:

$$
\begin{aligned}
R_{n,t,i,k} = \delta_{RRM,i,k} & + \sum_{j \neq i} \ln\left(1 + e^{\beta_{RRM,TT,k}\left(TT_{n,t,j} - TT_{n,t,i}\right)}\right) \\
& + \sum_{j \neq i} \ln\left(1 + e^{\beta_{RRM,LF,k}\left(LF_{n,t,j} - LF_{n,t,i}\right)}\right) \\
& + \sum_{j \neq i} \ln\left(1 + e^{\beta_{RRM,RA,k}\left(RA_{n,t,j} - RA_{n,t,i}\right)}\right) \\
& + \sum_{j \neq i} \ln\left(1 + e^{\beta_{RRM,RI,k}\left(RI_{n,t,j} - RI_{n,t,i}\right)}\right) \\
& + \sum_{j \neq i} \ln\left(1 + e^{\beta_{RRM,C,k}\left(C_{n,t,j} - C_{n,t,i}\right)}\right)
\end{aligned}
$$

Measurement equations I

- Did not include a deterministic component for the latent variable structural equation, motivated by a desire to not confound the drivers of decision rule heterogeneity with heterogeneity caused by socio-demographic factors
- Focussed on how well a respondent's current commute journey lined up with their aspirations
- Commute journeys evolve over time and can be assumed to be based on informed choices for most travellers
- Hypothesis is that a respondent who is more likely to be driven by regret is less likely to have settled on a current commute journey which performs poorly against their desired values on one or more key characteristics

Measurement equations II

$$I_{n,1} = TT_{n,1} - TT_{n,ideal} - \sum_{n=1}^{N} \frac{TT_{n,1} - TT_{n,ideal}}{N}$$

$$I_{n,2} = TT_{n,1} - TT_{n,acc} - \sum_{n=1}^{N} \frac{TT_{n,1} - TT_{n,acc}}{N}$$

$$I_{n,3} = \ln\left(FARE_{n,1}\right) - \ln\left(FARE_{n,ideal}\right) - \sum_{n=1}^{N} \frac{\ln\left(FARE_{n,1}\right) - \ln\left(FARE_{n,ideal}\right)}{N}$$

$$I_{n,4} = \ln\left(FARE_{n,1}\right) - \ln\left(FARE_{n,acc}\right) - \sum_{n=1}^{N} \frac{\ln\left(FARE_{n,1}\right) - \ln\left(FARE_{n,acc}\right)}{N}$$

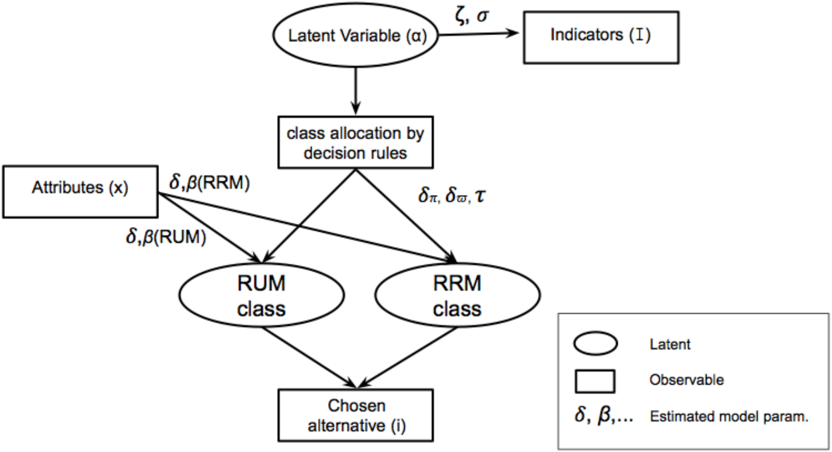
$$I_{n,5} = RA_{n,1} - RA_{n,ideal} - \sum_{n=1}^{N} \frac{RA_{n,1} - RA_{n,ideal}}{N}$$

$$I_{n,6} = RA_{n,1} - RA_{n,acc} - \sum_{n=1}^{N} \frac{RA_{n,1} - RA_{n,acc}}{N}$$

$$I_{n,7} = C_{n,1} - C_{n,ideal} - \sum_{n=1}^{N} \frac{C_{n,1} - C_{n,ideal}}{N}$$

$$I_{n,8} = C_{n,1} - C_{n,acc} - \sum_{n=1}^{N} \frac{C_{n,1} - C_{n,acc}}{N}$$

Model structure



Results: model fit

	Observations			
	choices	indicators	par	log-likelihood
RUM	3,680	0	7	-3,401.68
RRM	3,680	0	7	-3,402.59
LC ($K_s = 1, \forall s$)	3,680	0	15	-3,171.61
LC ($K_s = 2, \forall s$)	3,680	0	31	-3,025.64
Hybrid ($K_s = 2, \forall s$)	3,680	2,944	48	-9,533.25

Results: RUM choice model component

	base model			hybrid		
	est	rob. t-rat	$\frac{10\beta.}{\beta_{LF}}$	est	rob. t-rat	$\frac{10\beta.}{\beta_{LF}}$
$\delta_{\text{RUM},1,1}$	0.5345	3.32	-0.47	0.3462	1.91	-0.41
$\delta_{\text{RUM},2,1}$	-0.1014	-0.67	0.09	-0.0264	-0.18	0.03
$\beta_{\text{RUM},TT,1}$	-0.1475	-6.44	0.13	-0.1256	-7.30	0.15
$\beta_{\text{RUM},LF,1}$	-11.4640	-11.82	-	-8.5000	-5.71	-
$\beta_{\text{RUM},RD,1}$	0.0981	0.94	-0.09	-0.0907	-1.07	0.11
$\beta_{\text{RUM},ED,1}$	-0.3699	-4.53	0.32	-0.0852	-1.64	0.10
$\beta_{\text{RUM},C,1}$	-0.2653	-2.85	0.23	-0.1692	-1.91	0.20
$\delta_{\text{RUM},1,2}$	0.4063	1.90	-0.12	-0.3114	-1.30	2.38
$\delta_{\text{RUM},2,2}$	0.5492	1.83	-0.17	0.3820	2.83	-2.92
$\beta_{\text{RUM},TT,2}$	-0.0917	-4.12	0.03	-0.0299	-2.69	0.23
$\beta_{\text{RUM},LF,2}$	-32.9400	-4.05	-	-1.3103	-2.84	-
$\beta_{\text{RUM},RD,2}$	-0.5718	-2.40	0.17	-0.3550	-4.29	2.71
$\beta_{\text{RUM},ED,2}$	0.0253	0.51	-0.01	-0.1736	-3.11	1.32
$\beta_{\text{RUM},C,2}$	-0.5787	-2.05	0.18	-0.3365	-4.07	2.57
$\delta_{\pi,\text{RUM}}$	0	-	-	0	-	-
$\delta_{\varpi,\text{RUM},1}$	0.6274	1.97	-	0.3980	1.30	-
τ_{RUM}	-		-	0	-	-

Results: RRM choice model component

	base model			hybrid		
	est	rob. t-rat	$\frac{10\beta.}{\beta_{LF}}$	est	rob. t-rat	$\frac{10\beta.}{\beta_{LF}}$
$\delta_{RRM,1,1}$	-1.5751	-8.16	5.80	-1.6072	-8.30	5.78
$\delta_{RRM,2,1}$	-0.4866	-2.55	1.79	-0.4481	-2.42	1.61
$\beta_{RRM,TT,1}$	-0.0280	-3.49	0.10	-0.0276	-3.22	0.10
$\beta_{RRM,LF,1}$	-2.7138	-2.76	-	-2.7822	-2.97	-
$\beta_{RRM,RD,1}$	-0.2062	-3.05	0.76	-0.1872	-2.68	0.67
$\beta_{RRM,ED,1}$	-0.0577	-2.49	0.21	-0.0891	-1.91	0.32
$\beta_{RRM,C,1}$	-0.2238	-2.98	0.82	-0.2207	-3.24	0.79
$\delta_{RRM,1,2}$	0.3702	1.09	-3.57	-0.1386	-0.75	0.07
$\delta_{RRM,2,2}$	-0.3633	-2.87	3.50	-0.4404	-1.52	0.22
$\beta_{RRM,TT,2}$	-0.0201	-3.06	0.19	-0.0562	-4.89	0.03
$\beta_{RRM,LF,2}$	-1.0381	-3.47	-	-20.0590	-5.83	-
$\beta_{RRM,RD,2}$	-0.2367	-4.31	2.28	-0.1938	-1.60	0.10
$\beta_{RRM,ED,2}$	-0.0384	-1.40	0.37	-0.0682	-0.46	0.03
$\beta_{RRM,C,2}$	-0.1559	-3.15	1.50	-0.2747	-3.36	0.14
$\delta_{\pi,RRM}$	0.0450	0.27	-	-0.1127	-0.37	-
$\delta_{\varpi,RRM,1}$	0.0703	0.16	-	0.1361	0.49	-
τ_{RRM}	-		-	0.7600	2.57	-

Results: class allocation probabilities

	class allocation probabilities within rules			
	RUM-A	RUM-B	RRM-A	RRM-B
Base model	65.19%	34.81%	51.76%	48.24%
Hybrid 5%	-	-	-	-
Hybrid mean	59.82%	40.18%	53.40%	46.60%
Hybrid 95%	-	-	-	-

	overall					
	RUM-A	RUM-B	RRM-A	RRM-B	RUM	RRM
Base model	31.86%	17.01%	26.46%	24.66%	48.87%	51.13%
Hybrid 5%	12.05%	8.10%	8.95%	7.81%	20.15%	16.77%
Hybrid mean	31.59%	21.22%	25.20%	21.99%	52.82%	47.18%
Hybrid 95%	49.79%	33.44%	42.64%	37.21%	83.23%	79.85%

Results: measurement model

par	est	rob. t-rat
$\zeta_{\text{time ideal}}$	-3.0804	-2.41
$\sigma_{\text{time ideal}}$	15.176	8.71
$\zeta_{\text{time acceptable}}$	-3.7674	-3.15
$\sigma_{\text{time acceptable}}$	13.134	8.48
$\zeta_{\text{log-fare ideal}}$	-0.05814	-2.12
$\sigma_{\text{log-fare ideal}}$	0.39272	10.56
$\zeta_{\text{log-fare acceptable}}$	-0.07216	-2.00
$\sigma_{\text{log-fare acceptable}}$	0.4282	6.70
$\zeta_{\text{crowding ideal}}$	-0.94657	-5.33
$\sigma_{\text{crowding ideal}}$	2.4254	19.96
$\zeta_{\text{crowding acceptable}}$	-0.94933	-5.03
$\sigma_{\text{crowding acceptable}}$	2.2044	19.51
$\zeta_{\text{reliability ideal}}$	-2.2996	-14.80
$\sigma_{\text{reliability ideal}}$	1.0781	12.49
$\zeta_{\text{reliability acceptable}}$	-2.2985	-13.64
$\sigma_{\text{reliability acceptable}}$	0.85885	10.70

Conclusions I

- Results show a link between likely decision rule in SC scenarios and that respondent's stated satisfaction with the real world performance of their current commute journey
- Hypothesis that both outcomes (stated choices and stated satisfaction with real world choices) are influenced by deep rooted character traits
- Findings point towards a link between the tendency for regret minimisation and the effective minimisation of disparity with desired trip features for a respondent's real world commute journey
- Most regret-prone respondents in our sample have, to a larger extent, aligned their reference trip performance to their aspirational values

Conclusions II

- As with all hybrid structures, use of indicators as dependent rather than explanatory variables avoids risk of endogeneity bias, makes model suitable for forecasting and accommodates measurement error in the indicators
- Additionally. the causality link is very clear in our specific context
    - measures relating to satisfaction with the real life commute are meant to relate to the outcome of real world choice processes that are driven by the same character traits that also influence the choice processes in the stated choice component
    - different from an assumption that the satisfaction with real life commute journeys influences the choice of decision rule in the hypothetical choice scenarios
- Also some evidence of higher risk of confounding between heterogeneity in sensitivities and in decision rules in base model
- Reduced in hybrid model as any implied heterogeneity in decision rule also needs to be consistent with the measurement model component

Conclusions III

- A key issue remains the choice of appropriate indicators for the measurement component of the model, and here the onus is on analysts to make appropriate decisions at the survey design stage
- Richer set of indicators opens up possibilities of using multiple latent variables that relate to different character traits
- Also possibilities of linking the choice of decision rules to the values of presented alternatives, but this moves us away from the notion that the likely decision rule is influenced in particular by underlying character traits
- More work needed on actual implications of results, say in forecasting

Overall conclusions

- Big interest in decision rules in recent years
- Evidence that relative performance varies across datasets or even across people within the same data
- Big role for survey design and especially framing of opt outs
- Major issue remains how to use results from non-RUM models
- Need to remember benefits of RUM and fact that many of the traits might be able to be approximated by RUM

Questions . . .