The regret of not modelling regret: a Monte Carlo investigation

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Introduction

- The recent work by Chorus provides choice data analysts with an empirically tractable logit model of random regret minimization (RRM) choice behaviour in DCE.

- The model relaxes the assumption of utility maximization assuming that individuals aim to minimize their regret (defined as what one experiences when a non-chosen alternative performs better than the chosen one on one or more attributes).
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RRM models: a growing literature

- RRM is immediately comparable with RUM models
- Its use is becoming increasingly popular in transportation, environmental economics and health economics
- A tutorial on RRM has recently been published by Chorus in 2012
- Nlogit includes now routines for estimating RRM models.
Issues with RRM models

- No optimal experimental design for RRM;
- Estimating only RUM or RRM is not enough if we have a mix in the sample;
- Not sure if hybrid models capture choice paradigms or heterogeneity or confound them;
- The major issue within the RRM approach is that it is not suitable for welfare analysis (work in progress).
What is this study’s aim

- With this paper we explore the empirical bias caused by estimating a multinomial logit (MNL) model assuming that the data conforms either to the RUM or to the RRM choice behaviour only, whilst the data presents a mixture of the two choice paradigms.

- More specifically it is focused on the bias caused by:
  - estimating only RUM on data with different proportions of regret minimizers;
  - estimating only RRM on data with different proportions of utility maximizers;
  - On a side and not fully explored... hybrid models: is the bias problem solved?
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Choice modeling under RUM

Starting from the generic Utility function (RUM - McFadden, 1974)

\[ U_{nit} = V(\beta, \vec{x}_{nit}) + \epsilon_{nit}, \]

MNL models in this framework are:

\[ \Pr_{nit}^{RU} = \frac{e^{\beta' \vec{x}_{nit}}}{\sum_{j=1}^{J} e^{\beta' \vec{x}_{njt}}}. \]
Choice modeling under RRM

The systematic part of anticipated regret is defined as:

\[ R_{nit} = \sum_{j \neq i} \sum_{m=1}^{M} \ln \left( 1 + \exp(\theta_m \delta_{ij}) \right), \text{ where } \delta_{ij} = x_{njmt} - x_{nmit}. \]

The derived logit choice probability based on regret (Chorus, 2010) is:

\[ Pr_{nit}^{RR} = \frac{e^{-R_{nit}}}{\sum_{j=1}^{J} e^{-R_{njt}}}. \]
Design of Monte Carlo experiment

- We simulated 11 different data generating processes (DGP)
- For each DGP we simulate 1,000 samples of 493 individuals observed over 10 choices

The DGP for both RUM and RRM is based on Boeri et al. (2013): a study in health economics aimed at testing the trade-off that people are willing to make between life style choices, in terms of diet, physical activity, and the risk of dying from cardiovascular disease in the next 10 years.

Boeri et al. (2013):

The experiment

The simulated dataset is based on:

**Table:** Results from RUM-logit and RRM-logit models for real data; 4,930 observations

<table>
<thead>
<tr>
<th></th>
<th>RU</th>
<th>RR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>−0.0985</td>
<td>−0.0616</td>
</tr>
<tr>
<td>Increase in Physical Activity</td>
<td>0.0013</td>
<td>0.000816</td>
</tr>
<tr>
<td>Fat reduction</td>
<td>0.0024</td>
<td>0.0017</td>
</tr>
<tr>
<td>Risk of sheart attack in next 10 years</td>
<td>−0.0783</td>
<td>−0.0537</td>
</tr>
<tr>
<td>$\mathcal{L}(\hat{\beta})$</td>
<td>−5,280.37</td>
<td>−5,275.37</td>
</tr>
</tbody>
</table>
Indicators

We report 3 indicators of the bias of the estimations from the DGP:

- $\text{Bias}(\hat{\tau}) = 1/R \sum_{1}^{R} (\hat{\tau}^r - \tau)$;
- average of the absolute relative error: $\overline{RAE} = 1/R \sum_{1}^{R} |(\hat{\tau}^r - \tau) / \tau|$;
- fraction of $\hat{\tau}^r$ falling within 10% interval around the true value; $\Gamma_{0.05} = 1/R \sum_{1}^{R} d(\tau^r \in \tau \pm \tau \times 0.05)$

where:
R = number of samples simulated (1000)
$\tau$ is the true value and $\hat{\tau}^r$ is the rth value estimated in the experiment
$d$ is an indicator function
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Impacts on estimates from a RUM-logit model

Parameters Bias

WTP Bias

10% Interval around real value
Impacts on estimates from a RRM-logit model

![Graphs showing MSE and RAE with varying RUM percentages]

![Graphs showing Bias and R'M interval with varying RUM percentages]
Impacts on estimates from a Hybrid model—RUM part

**Parameters Bias**

- cost
- fat
- exe
- risk

**WTP Bias**

- w_fat
- w_exe
- w_risk

**10% Interval around real value**

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Impacts on estimates from a Hybrid model—RRM part

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RAE

Bias

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This paper looked at how the presence of both RUM and RRM can bias results from DCE.

We found:

- The higher the proportion of regret minimizers in the sample the higher bias for RUM estimations.
- Within RRM bias decreases up to a point and then increases again increasing the proportion of regret minimizers in the sample.
- Interesting and conceptually counterintuitive: the bias is not as strong on willingness to pay estimates as it is found to be on parameter estimates.
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We also found:

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Future Work

- Derive (develop) welfare measures within RRM
- Work on a better design for SP data analysis
- Understand better how hybrid models in practice (LC) can help with the bias
- Work with RP data in the same directions
- Experimental economics (can RRM help?)
Thank you for your attention!!!

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Questions???

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