# A Monte Carlo investigation on the impact of not modelling Regret

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# Introduction

- The recent work on regret (Starting from Chorus and colleagues) provides choice data analysts with an empirically tractable logit model of random regret minimization (RRM) choice behavior.

- 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).

# 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 behavior only, whilst the dataset 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 RRM;
  - estimating only RRM on data with different proportions of RUM;
  - hybrid models: can they solve the bias problem?

- On a side and not fully explored…
  - Should we include Profundity of regret? Could it help?

# Methodology

# Methodology: RUM

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

$$U_{nit} = V\left(\beta, \vec{x}_{nit}\right) + \epsilon_{nit},$$

- MNL models in this framework are:

$$\Pr_{nit}^{RU} = \frac{e^{\beta' \vec{x}_{nit}}}{\sum_{j=1}^{J} e^{\beta' \vec{x}_{njt}}}.$$

# Methodology: RRM

- Starting from the Chorus 2010 (regret can be defined as)

$$R_{nit} = \sum_{j \neq i} \sum_{m=1 \ldots M} \ln\left(1 + \exp(\theta_m \delta_{ij})\right), \text{ where } \delta_{ij} = x_{njmt} - x_{nimt}.$$ (Chorus, 2010)

- MNL models in this framework are:

$$\Pr_{nit}^{RR} = \frac{e^{(-R_{nit})}}{\sum_{j=1}^{J} e^{\left(-R_{njt}\right)}}.$$

# 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):

Boeri, M., Longo, A., Grisolia, J., Hutchinson, W. and Kee, F. (2013)
The role of regret minimization in lifestyle choices affecting the risk of coronary heart disease, *Journal of Health Economics*, **32**(1): 253–260.

# Design of Monte Carlo experiment

The simulated dataset is based on:

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

| | **RU** | **RR** |
|---|---|---|
| | *Coeff. Est.* | *Coeff. Est.* |
| Cost | −0.0985 | −0.0616 |
| Increase in Physical Activity | 0.0013 | 0.000816 |
| Fat reduction | 0.0024 | 0.0017 |
| Risk of sheart attack in next 10 years | −0.0783 | −0.0537 |
| $\mathcal{L}(\hat{\beta})$ | −5,280.37 | −5,275.37 |

# Efficiency indicators

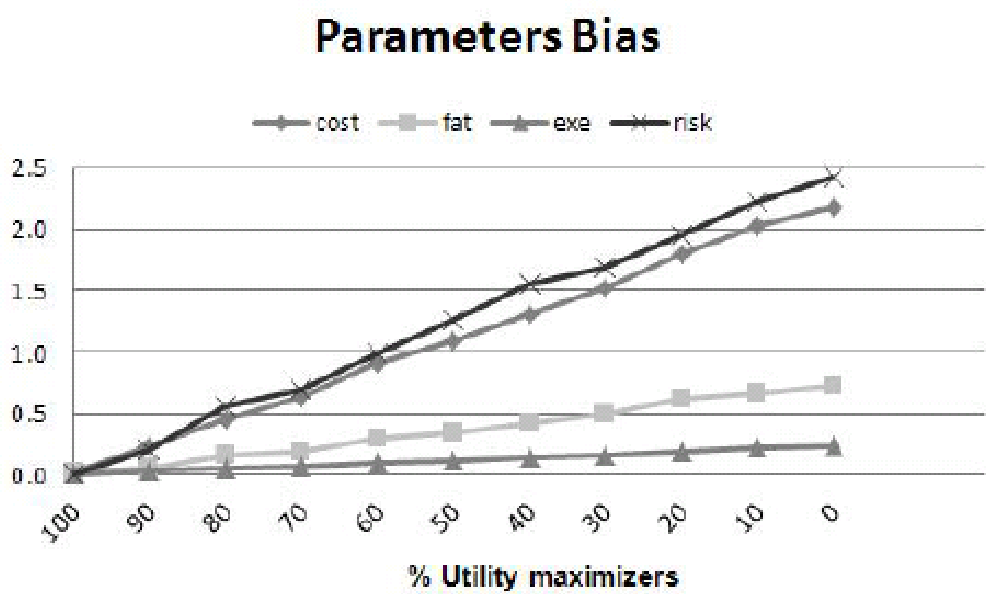
- We report 3 efficiency indicators:

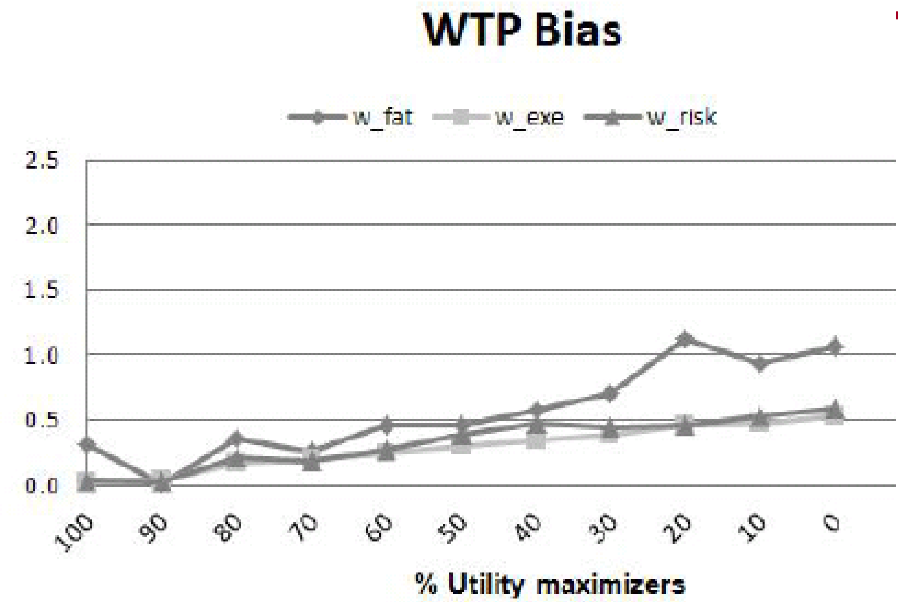
  - $Bias(\hat{\tau}) = 1/R\sum_1^R(\hat{\tau}^r - \tau)$;
  - average of the absolute relative error: $\overline{RAE} = 1/R\sum_1^R|(\hat{\tau}^r - \tau)/\tau|$;
  - fraction of $\hat{\tau}^r$ falling within 10% interval around the true value; $\Gamma_{0.05} = 1/R\sum_1^R d(\tau^r \in \tau \pm \tau X0.05)$

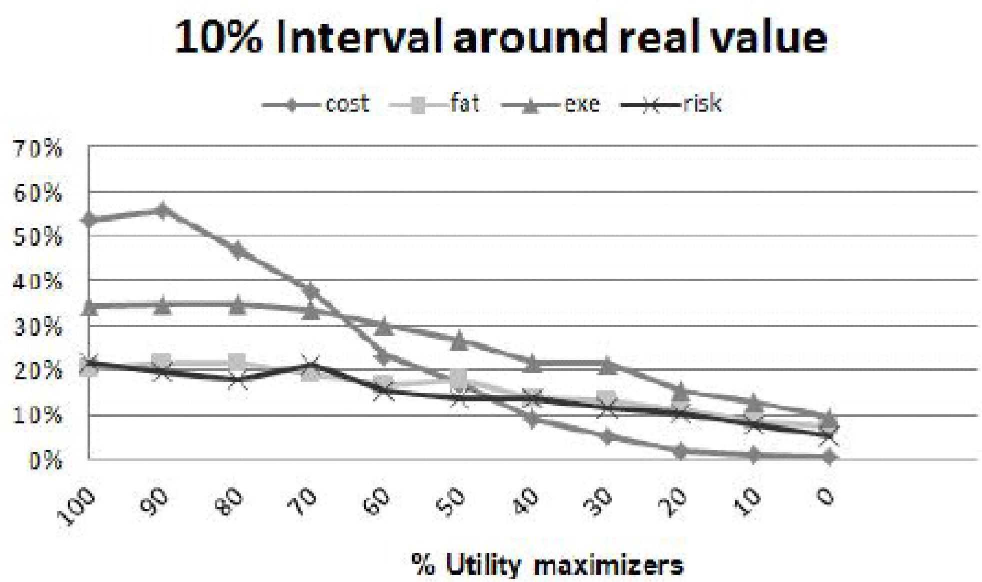
where:
R = number of samples simulated (1000)
$\tau$ is the true value and $\hat{\tau}^r$ is the rth value estimated in the experiment
$d$ is an indicator function

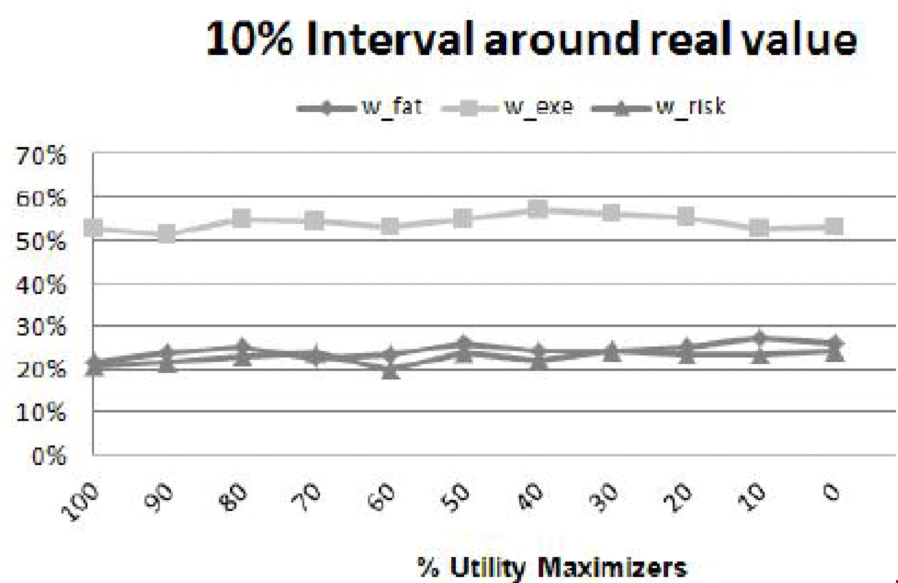
# Results

# Impacts on estimates from a RUM-logit model

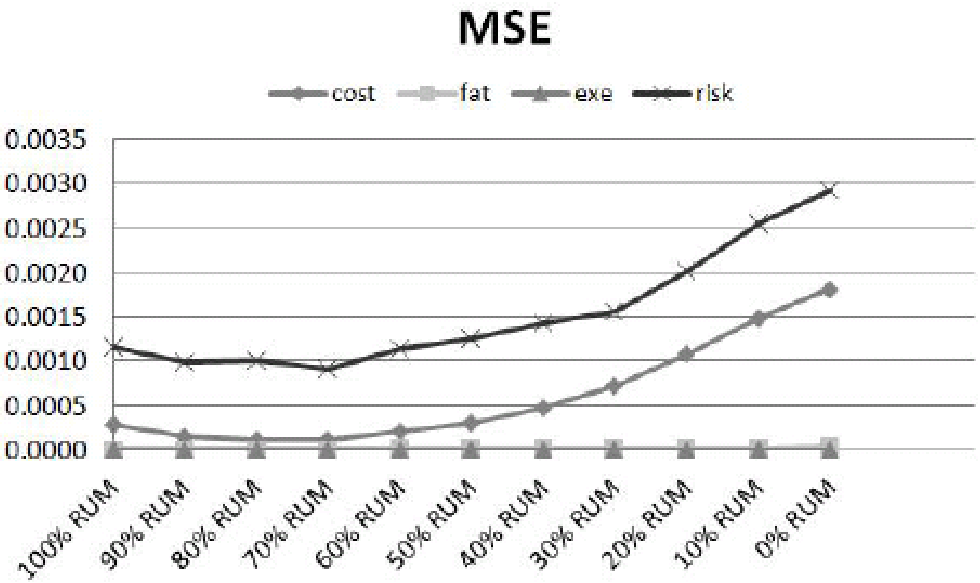


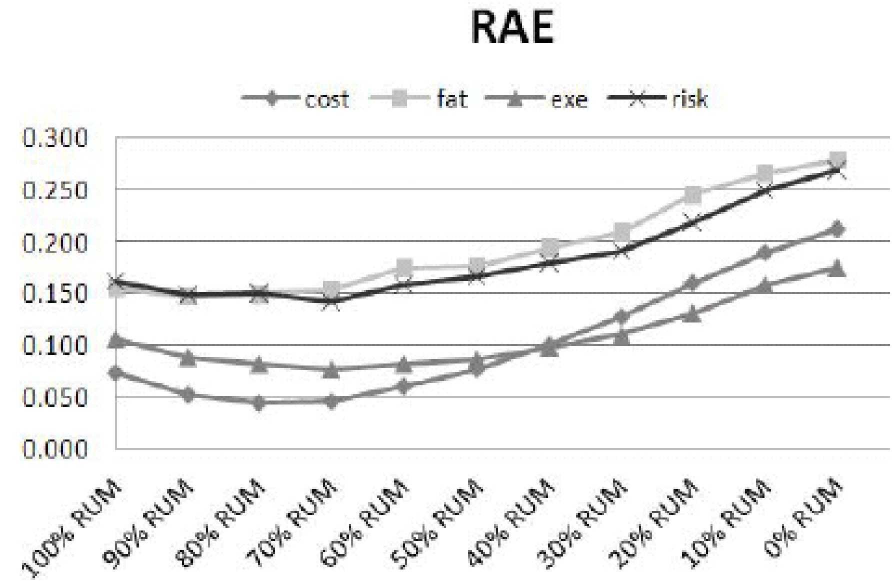



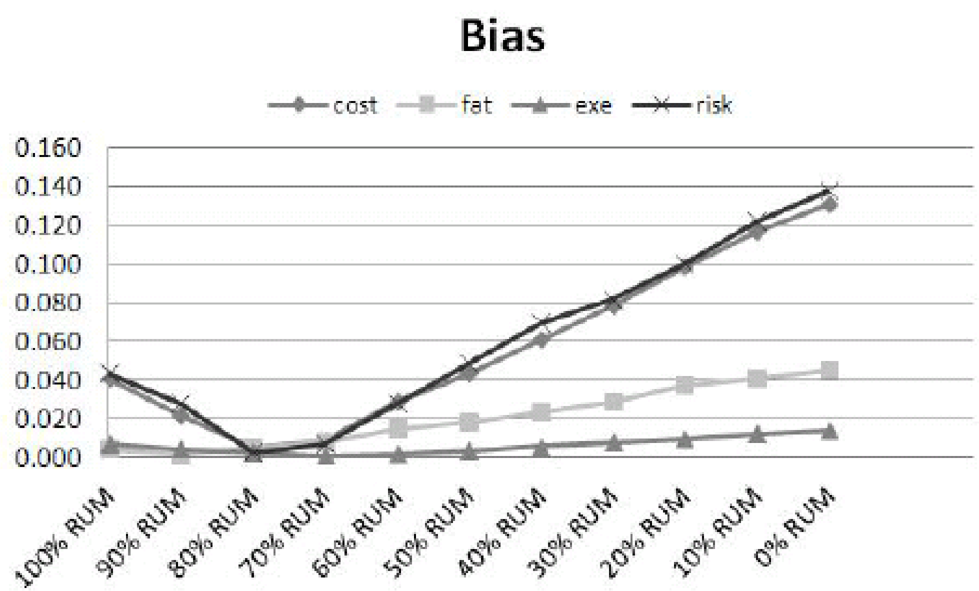



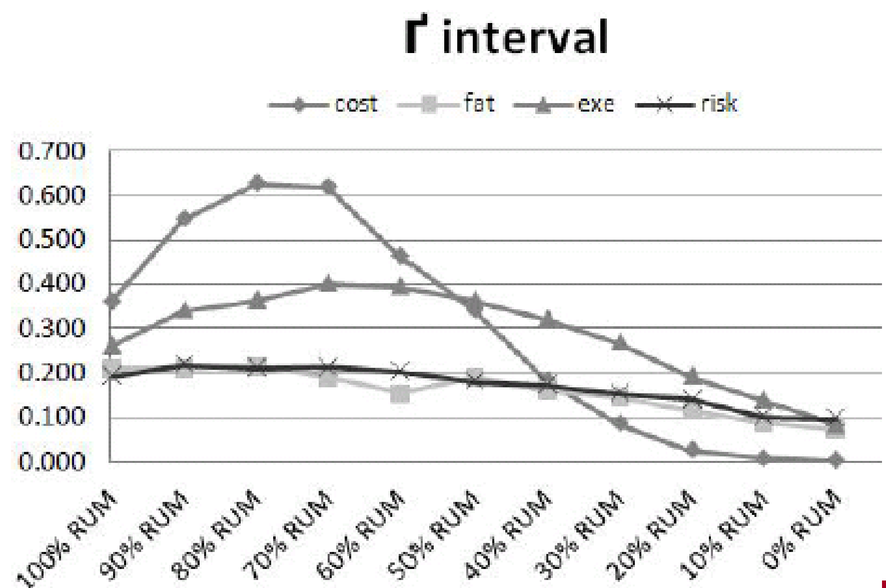



# Impacts on estimates from a RRM-logit model

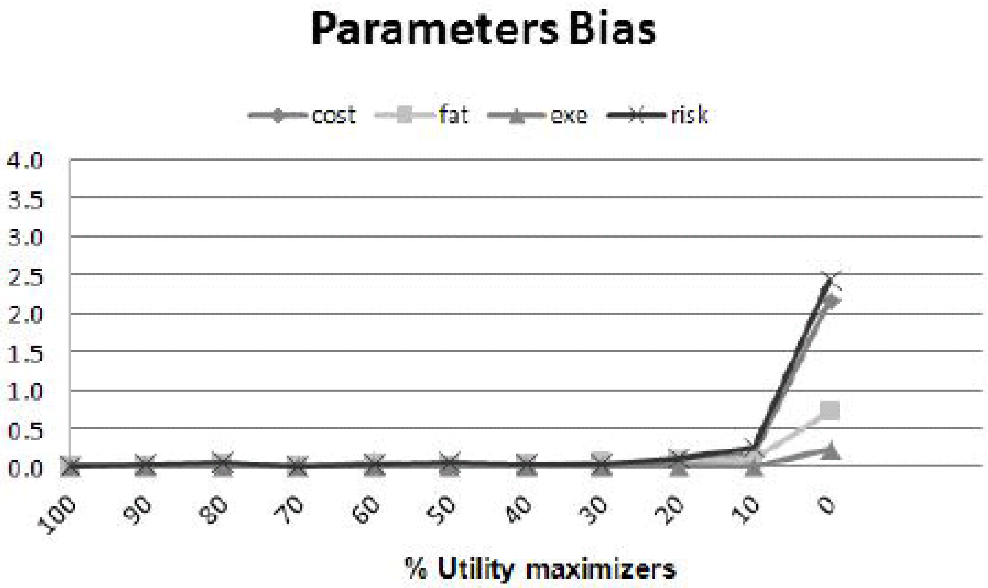


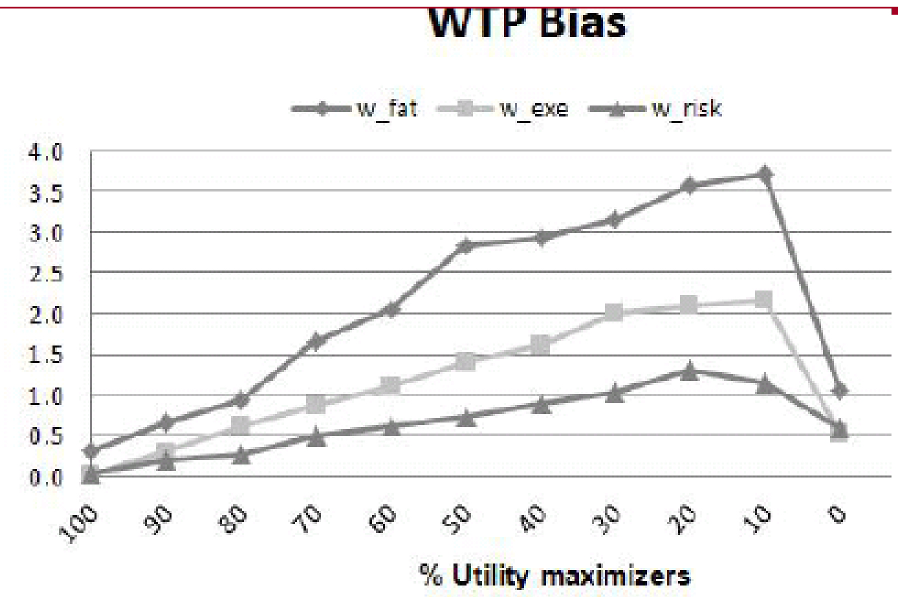



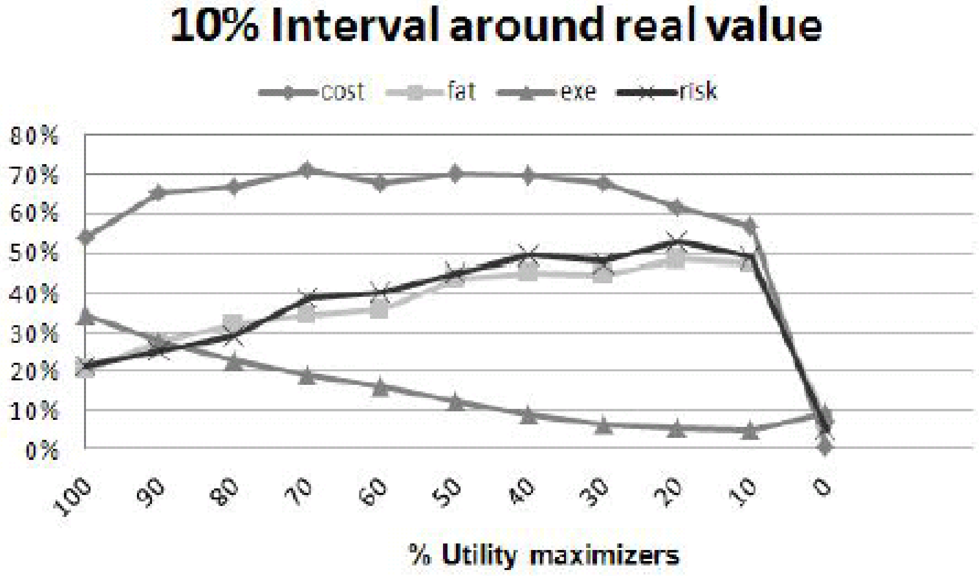



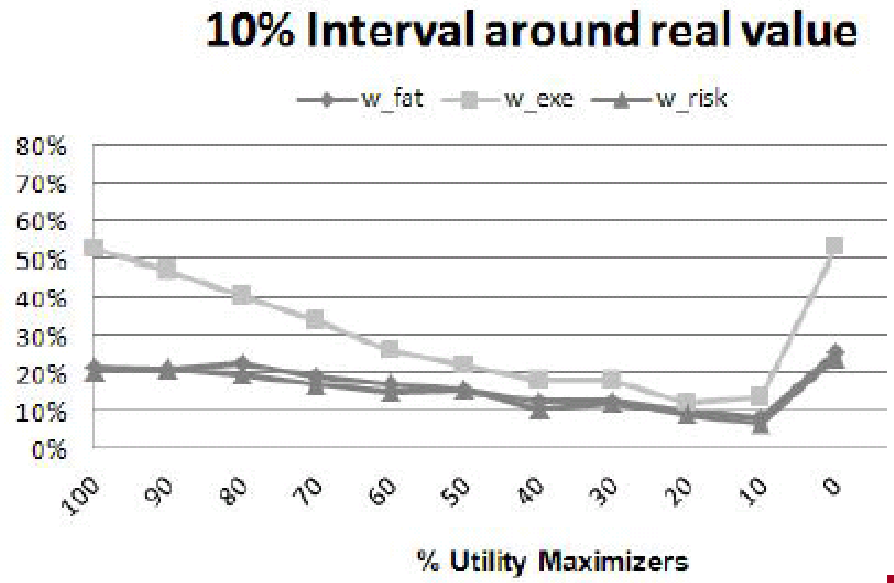



# Impacts on estimates from a Hybrid model—RUM part

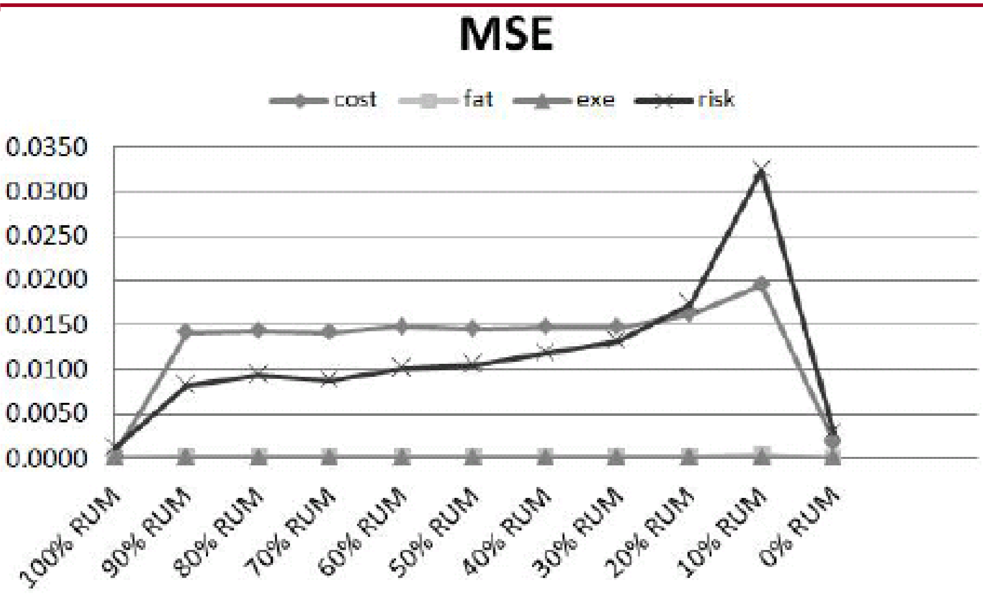


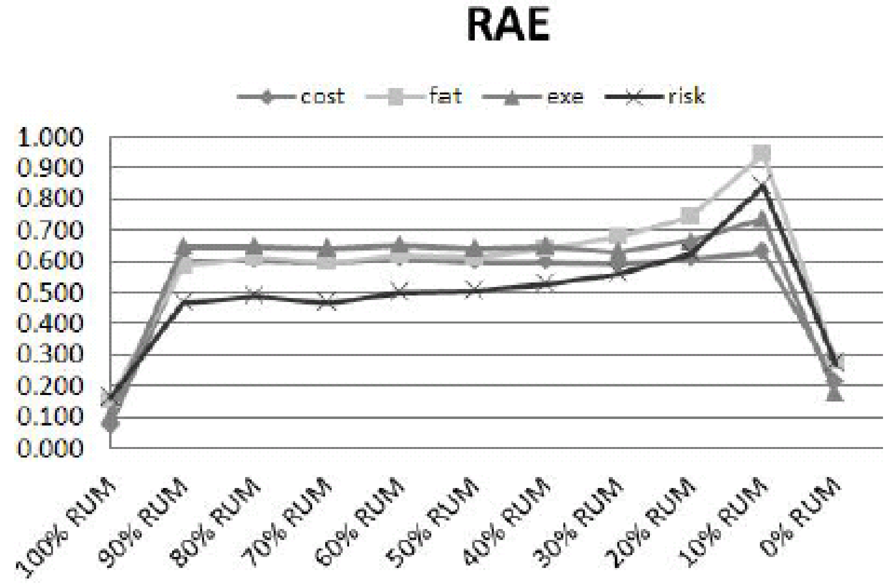



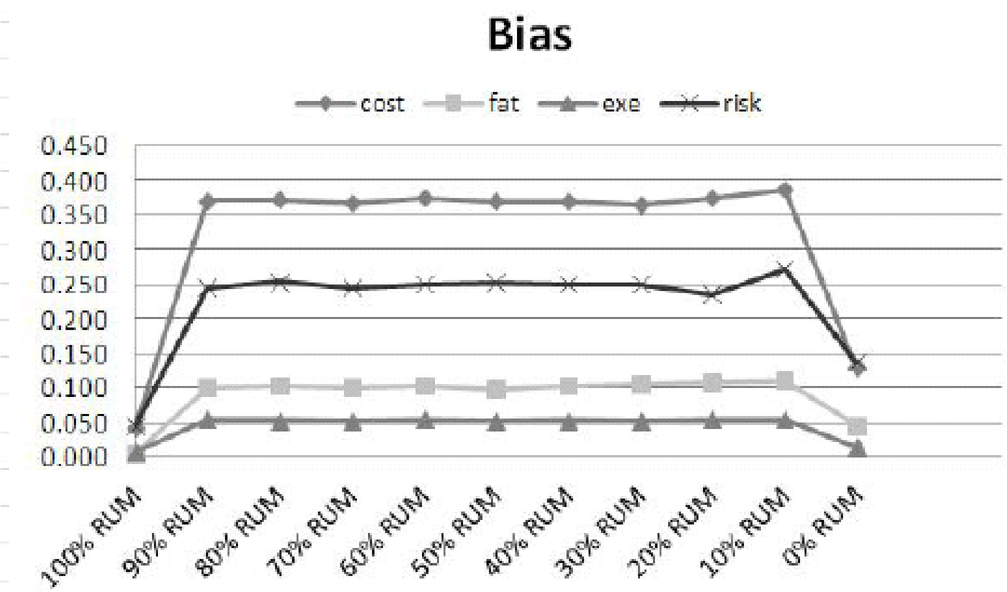



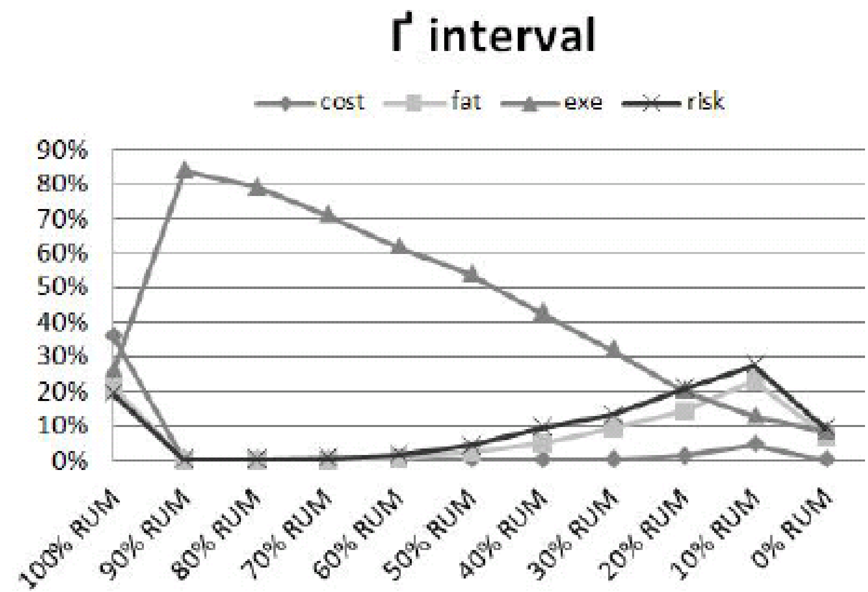



# Impacts on estimates from a Hybrid model—RRM part



# Conclusions & future work

# Conclusions

- 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

    ==> Design?
- **Interesting and (maybe) conceptually counterintuitive:**
  - the bias is not as strong on willingness to pay estimates as it is found to be on parameter estimates.
- **We also found:**
  - Hybrid models (assuming we know who uses RRM ad who RUM) can help reducing this bias for RUM, but It does not work on RRM models (design?)
  - Scale increases as % RUM increases

# Future work

- Understand the RRM part of the simulation (what is going on? Can we retrieve the DGP?)
  - Find the right DGP & settings for the experiment…
- Include scale RRM
  - (can it be used as a test? Combined with hybrid to study both sample – scale – resp. – hybrid)
- Finalize the study for a manuscript (is there a contribution? Which would be the best target audience and journal)
  - Ideas?