The impact on welfare analysis of not modelling scale heterogeneity: a Monte Carlo experiment

Marco Boeri[1,3] and Alberto Longo[1,2]

[1] Queen's University Belfast, Belfast

[2] BC3, Basque Centre for Climate Change, Bilbao, Spain

[3] Health Preference Assessment Group, RTI Health Solutions, Research Triangle Park, NC USA

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Introduction

- Multinomial Logit models (MNL) are the starting point for analysing Discrete Choice Experiments (DCE).
- The assumption of scale heterogeneity across subgroups or individuals has been widely discussed in the literature and have given rise to Heteroscedastic MNL models:
  - discrete Heteroscedasticity (Swait and Louviere, 1993; Swait and Adamowicz, 2001)
  - continuous Heteroscedasticity (Breffle and Morey, 2000)
- No previous study has measured the bias that the presence of heterogeneity in scale factor can cause on simple MNL models.

What this is not about

- This study is not about accommodating for both scale and preference heterogeneity in one model.
- On going debate this study is not contributing to:
  - "Addressing only one source of heterogeneity negates the fact that true choice behaviour is likely to be in some middle ground with some variation in scale and some in taste" (Thiene and Scarpa, 2010)
    - the generalised multinominal logit model (GMNL) (Fiebeg et al., 2010)
    - the scale-adjusted LC model (Magidson and Vermunt, 2007; Campbell et al., 2011)
    - the WTP-space model (Train and Weeks, 2005).
- "efforts to separately identify random scale heterogeneity have been misguided. Econometrically, a linear in parameters specification of the logit model perfectly confounds scale with taste sensitivity" (Hess and Rose, 2012)

What is this study's aim

- Aim of the study:

  To measure the bias caused by estimating MNL and HMNL models on datasets generated including scale.

- More specifically it is focused on the bias caused by:
  - not accommodating for the presence of a different scale parameters across groups (discrete scale heterogeneity);
  - not accommodating for the presence of individual scale parameters (continuous scale heterogeneity);

Methodology

Methodology: MNL and HMNL models

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

$$U_{nit} = V(\beta, x_{nit}) + \varepsilon_{nit}$$

- MNL and HMNL models:

$$\Pr(i_{nt}) = \frac{\exp(\lambda_{ni} \cdot \beta' x_{nit})}{\sum_{j=1}^{J} \exp(\lambda_{ni} \cdot \beta' x_{nit})}$$

- Scale heterogeneity can be:
  - absent - fixed to 1 (MNL model)
  - discrete (Swait and Adamowicz, 2001)
  - continuous (Breffle and Morey, 2000)

Design of Monte Carlo experiment

- We simulate 1,000 samples of 1,200 individuals observed over 8 choices, based on different data generating processes (DGP)
- (we have simulated 8 different DGP, this will focus on the first:)
  - 1 DGP based on HMNL with discrete scale heterogeneity based on 3 groups—specifically scale equal to 1, 0.5 and 2;
  - 1 DGP based on HMNL with continuous scale heterogeneity based on Breffle and Morey (2000)—e.g.scale parameter lognormal distributed with mean exp(0) and sigma 0.65;
  - 4 DGP based on preference heterogeneity for one attribute (over 4) each time;
  - 1 DGP based on preference heterogeneity for one attribute and the cost;
  - 1 DGP based on preference heterogeneity for all attributes (4)

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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:
    $\overline{RAE} = 1/R\sum_1^R|(\hat{\tau}^r - \tau)/\tau|$;

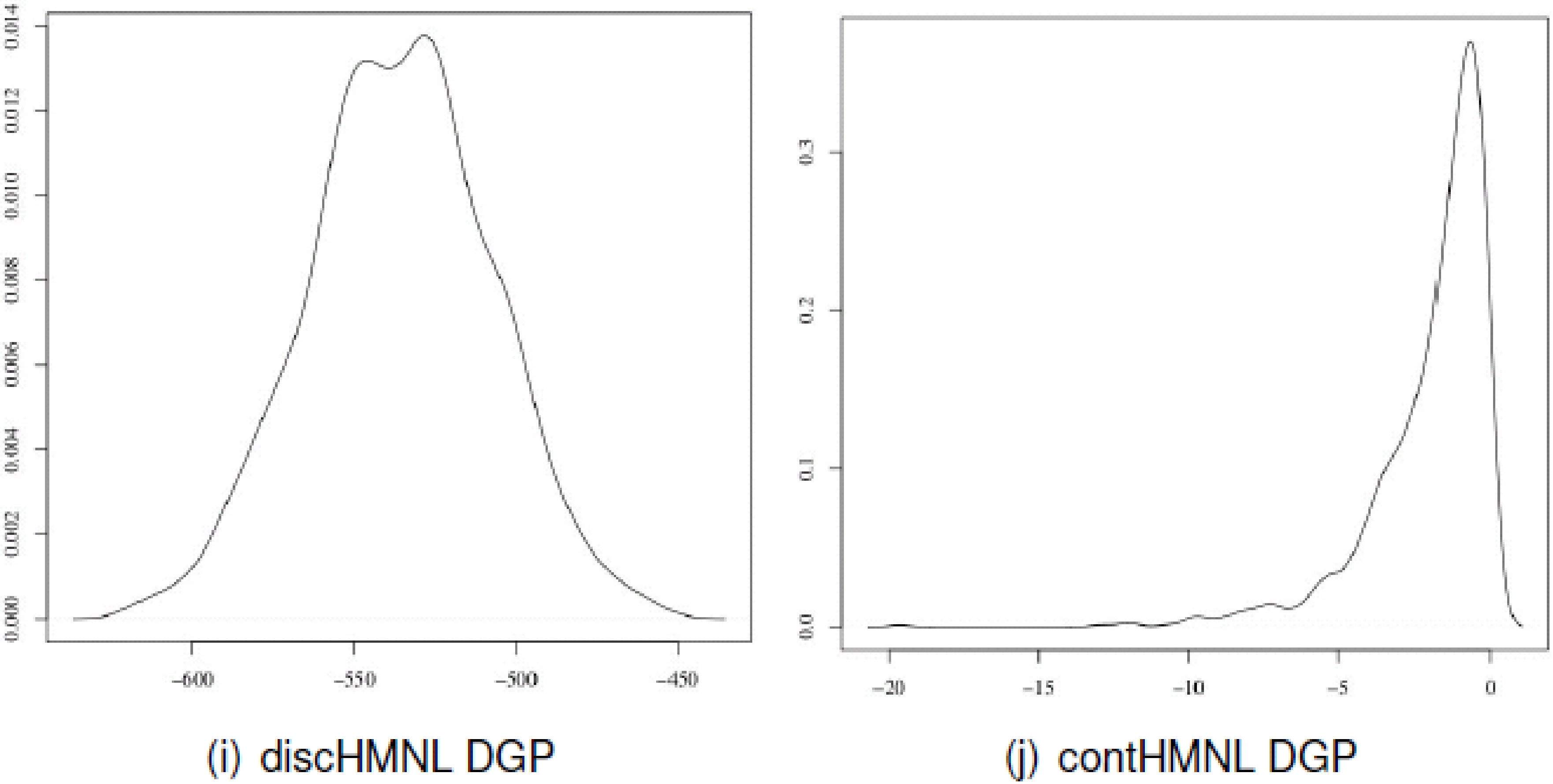
  - fraction of $\hat{\tau}^r$ falling within 10% interval around the true value;
    $\Gamma_{0.05} = 1/R\sum_1^R d(\tau^r \in \tau \pm \tau X0.05)$

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

The experiment

- For the simulated dataset we have drawn inspiration from a study on tap water supply. The simulated dataset is based on:
- 3 alternatives
- 3 attributes each alternative:
  1. INT - Internal sewer flooding - set at $\mu = -0.3$;
  2. EXT - External sewer flooding - set at $\mu = -0.5$;
  3. NUI - Nuisance from sewage treatment - set at $\mu = 0.8$
  4. BIL - Water bill - set at $\mu = -0.03$
- Sample of 1,200 respondents.
- 8 choice sets per respondent (9,600 observations).

Model fit - differences in Log-likelihood (MNL - HMNL)



Efficiency indicators for MNL and HMNL on DGP with scale heterogeneity

Parameter	BIAS	RAE	$\Gamma_{0.05}$	Parameter	BIAS	RAE	$\Gamma_{0.05}$
MNL on discrete HMNL				MNL on continuous HMNL			
β_{INT}	0.0220	0.0741	0.27	β_{INT}	0.0247	0.0828	0.22
β_{EXT}	0.0461	0.0922	0.03	β_{EXT}	0.0503	0.1005	0.05
β_{NUI}	-0.0721	0.0901	0.01	β_{NUI}	-0.0800	0.1000	0.02
β_{BIL}	0.0130	0.4577	0.06	β_{BIL}	0.0150	0.5198	0.03
W_{INT}	72.38	10.62	0.06	W_{INT}	-43.18	7.79	0.04
W_{EXT}	114.37	10.17	0.06	W_{EXT}	-68.36	7.55	0.05
W_{NUI}	-184.72	10.24	0.06	W_{NUI}	112.45	7.65	0.06
HMNL on discrete HMNL				HMNL on continuous HMNL			
β_{INT}	-0.0005	0.0340	0.75	β_{INT}	0.0243	0.0840	0.26
β_{EXT}	-0.0012	0.0267	0.86	β_{EXT}	0.0497	0.1001	0.12
β_{NUI}	0.0012	0.0230	0.91	β_{NUI}	-0.0790	0.0991	0.09
β_{BIL}	-0.0007	0.2468	0.15	β_{BIL}	0.0150	0.5187	0.04
W_{INT}	12.01	1.60	0.12	W_{INT}	13.02	5.93	0.04
W_{EXT}	20.67	1.64	0.14	W_{EXT}	20.43	5.71	0.05
W_{NUI}	-33.16	1.64	0.14	W_{NUI}	-33.74	5.76	0.05

Conclusions

Conclusions

- This paper looked at how not considering scale heterogeneity biases estimations and welfare analysis

- Results are in line with expectations:
  - Estimating MNL on datasets that include discrete scale heterogeneity creates bias, especially on cost coefficient and therefore on welfare analysis
  - **This is avoided by estimating HMNL models**
  - Also estimating MNL on datasets that include continuous scale heterogeneity create bias
  - **This is not solved by the HMNL, which can in fact mislead analyst's conclusions (should look at LL improvement).**

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