Conjoint Rating, Ranking and Choice: Selected Theoretical and Empirical Pitfalls

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Outline of the presentation

- Motivation
- Pitfalls on Empirical Issues of Conjoint Choice, Rating and Ranking
- Monte Carlo Studies
- Future Research

Motivation

Conjoint Choice, Ranking and Rating are widely used. Their theoretical backgrounds and empirical implementation have to be addressed.

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This presentation tries to shed some (*partially, new*) light on the issue. This lecture concentrates on the two issues:

Efficient Estimation of conjoint-study data;

Variable Selection Problem in conjoint studies.

Efficient Estimation

Multivariate LDV models

It becomes recognized that random-effect / random-parameters multivariate LDV models are theoretically correct approaches to estimation.

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Efficient estimation

Efficient estimation of MLDV models require an evaluations of multivariate integrals. What are the possibilities?

Variable Selection Problem

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Our contribution

We evaluate selected methods for VSP in the conjoint setting using a **Monte Carlo study**.

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1. We do not consider behavioral biases;
   thus we evaluate procedures `as if` the usual neoclassical assumptions hold.
2. This is by no means a complete survey of the field; rather it contributes to highlight selected issues.

The Case for MLDV Models - I

The Quest

Are Contingent Ratings' Results Identified under the Neoclassical Paradigm?

The Case for MLDV Models - I

The Quest

Are Contingent Ratings' Results Identified under the Neoclassical Paradigm?

Answer

It depends on the estimation procedure used:

OLS-based approaches (such as linear SUR or Tobit models) preclude identification of the WTP;

Ordered Probit enables it.

The Case for MLDV Models - II

Even if the Ordered Probit enables the Conjoint Rating Identification, there are practical problems, such as

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Therefore Conjoint Ranking or Choice might be preferable strategy.

Note that even under the alternatives, responders answer several questions, thus a random-effect LDV model might be a possible choice.

An Example - Random-Effect Probit Model

Model formulation

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How to approximate the Integral?

A possible approximation:

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$$\cong \sum_{c_n} \prod_{i=1}^{I} \varphi(y_i^{(n)}|X_n, c_n, \beta) w(c_n).$$

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How to generate c_n, $w(c_n)$?

- quadrature-base rules,
- pseudo-Monte Carlo integration (pseudo random sequence)
- quasi-Monte Carlo integration (low discrepancy methods)

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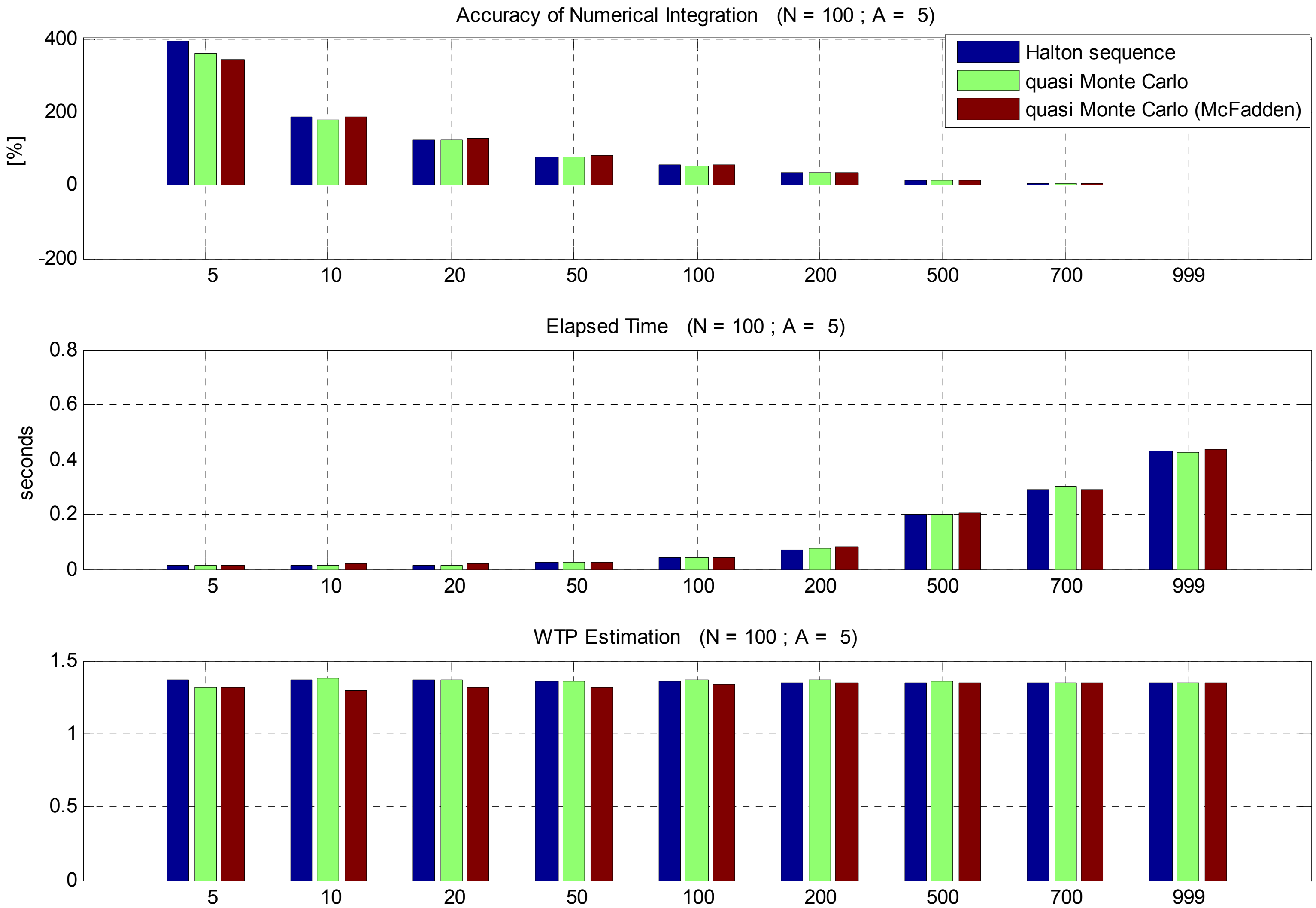
Design of the Monte Carlo Study I

Design

We use Lusk (2002) AJAE model extended by the random effect parameter.

We compare three methods of approximations of (1):

1. pseudo MC based on Halton sequences;
2. quasi Monte Carlo;
3. quasi Monte Carlo (McFadden, 1989 simulator).


Accuracy of Numerical Integration (N = 100 ; A = 5)
[%]
400
200
0
-200
5
10
20
50
100
200
500
700
999
Halton sequence
quasi Monte Carlo
quasi Monte Carlo (McFadden)
Elapsed Time (N = 100 ; A = 5)
seconds
0.8
0.6
0.4
0.2
0
WTP Estimation (N = 100 ; A = 5)
1.5
1
0.5
0

Results of the Monte Carlo Study I

Findings - I

Contrary to Train (1998) and (1999) we find that the qMC methods does not seem to outperform the pMC approaches significantly (both in the expected accuracy and the approximation variance).

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A Conjecture

?The product rule in (1)? drives down the advantage of low discrepancy methods.

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A Conjecture

?The product rule in (1)? drives down the advantage of low discrepancy methods.

Future research

To try qMC methods other than low-discrepancy approaches (such as Weyl or Haber sequences).

Results of the Monte Carlo Study I

Findings - II

We confirm that the McFadden (1989) approach to simulated maximum likelihood outperforms the pMC integration with identical draws over individuals.

Conclusion I

For a large class of MLDV, the conventional pMC is a sufficient tool and there seems to be a little efficiency using more elaborated algorithm.

- This holds especially if the pMC integration is done efficiently;
- on the other hand, the only costs of the qMC are fixe-costs of learning by the researcher.

A Never-ending Battle with Model Selection

The Quest

How to Select Correct Regressors to a Model

A Never-ending Battle with Model Selection

The Quest

How to Select Correct Regressors to a Model

- The purpose matter: forecasting versus structural analysis
- A neglected issue in non-linear models (because of complexity?)

Design of the Monte Carlo Study II

Design

We use again Lusk (2002) AJAE model extended by ‘false’ variables correlated with the true ones.

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We use again Lusk (2002) AJAE model extended by ‘false’ variables correlated with the true ones.

The procedures are programmed in GOAT TOOLBOX$^{\text{TM}}$ programmed by me.

Approach of this study

It is hard to evaluate model selection procedures analytically: we use the Monte Carlo approach.

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We use the four methods

- Penalized Likelihood (AIC and BIC panalties)
- Cross Validation Approaches (leave one CV_1 and leave 25% $CV_{0.25}$)

Results of the Monte Carlo Study - II

Results

Penalized Likelihoods are too conservatives: they choose larger models than necessary.

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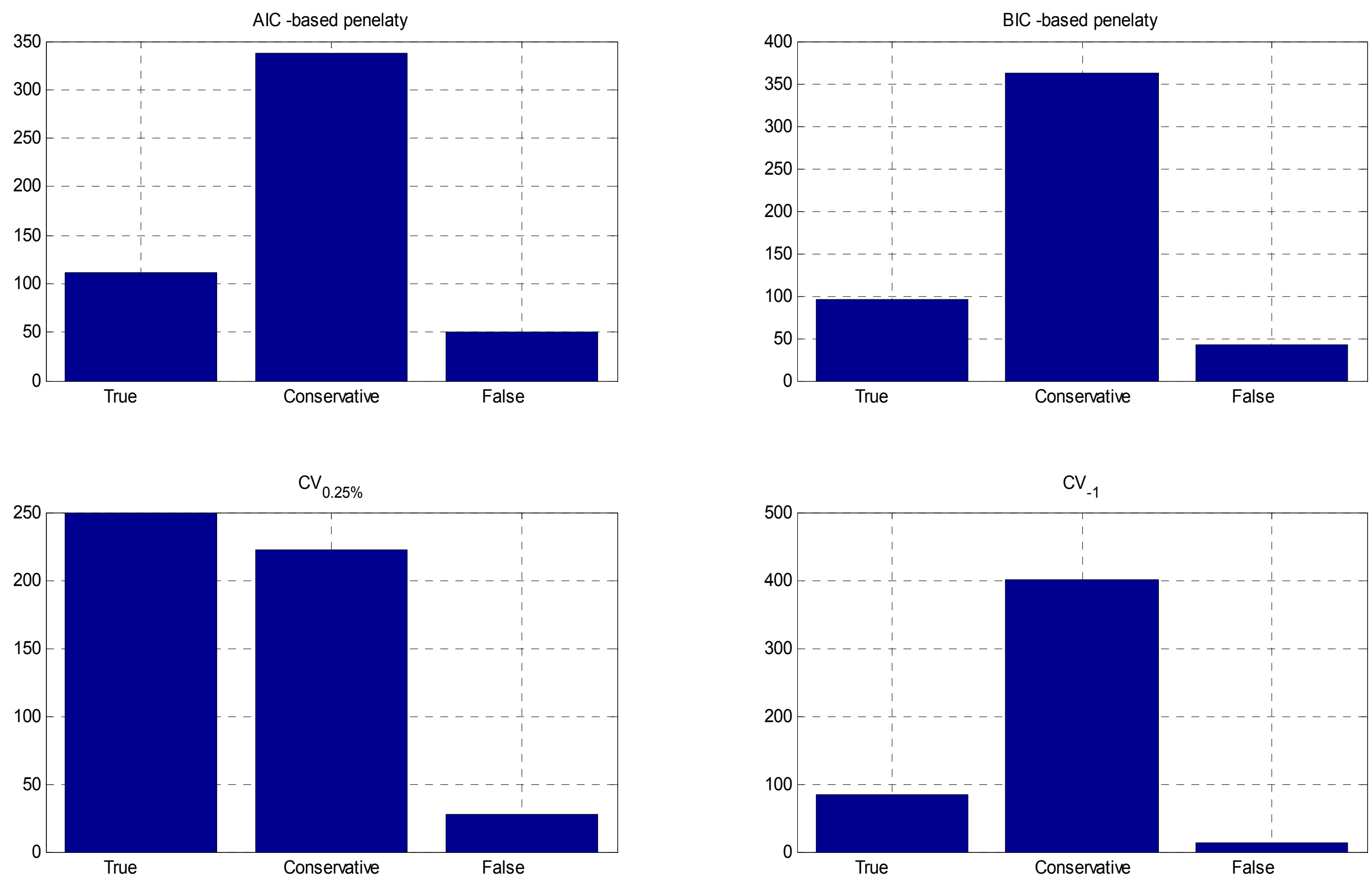
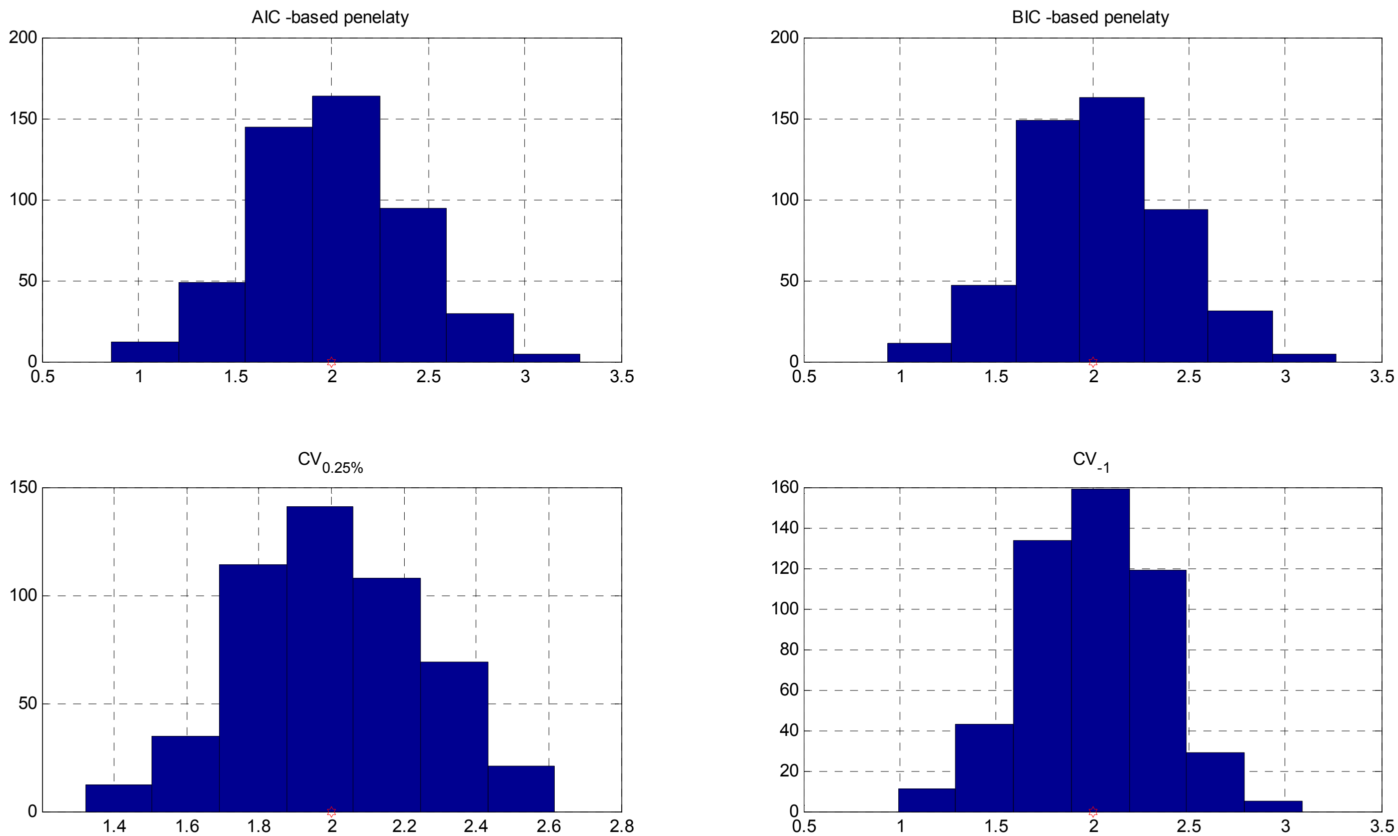
Results

The $CV_{0.25}$ outperforms CV_1.

The results confirms Shao (1996, 1997) analyses for linear systems.



AIC -based penelaty
BIC -based penelaty
$CV_{0.25\%}$
CV_{-1}
True
Conservative
False
0
50
100
150
200
250
300
350
400
500



AIC -based penelaty
BIC -based penelaty
CV0.25%
CV-1
0
50
100
150
200
0.5
1
1.5
2
2.5
3
3.5
1.4
1.6
1.8
2.2
2.4
2.6
2.8
20
40
60
80
120
140
160

Planned future research - MLDV models

The qMC applications usually use the low-discrepancy methods, such as Halton sequences, to approximate integrals in MLDV likelihoods.

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Future research

To try quadrature and qMC methods other than low-discrepancy approaches.

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We will try to extend the GOAT TOOLBOX$^{\text{TM}}$ to include not only variable selection (given functional form) procedures, but also selection procedures to choose a functional form.

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We will try to extend the GOAT TOOLBOX™ to include not only variable selection (given functional form) procedures, but also selection procedures to choose a functional form.

Non-parametric problem

To check CV_1 against $CV_0.25$ in non-parametric setting (latent class models, mixed logit).

Forecasting problems

We plan to incorporate White (2000) reality check for data snooping (against a parsimonious specifications).

Comments are welcomed.

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