A novel, utility-based, discrete choice model of satisficing behavior

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Motivation

- Discrete choice models are frequently used to analyze individuals' preferences
  - They can identify various types of behavior from different data sources
  - They are not limited to the lab setting
- Nevertheless, most models employ a random utility specification
  - Assume that individuals are rational, evaluate all the alternatives and maximize their utility
    - Not very realistic in light of behavioral research
  - Allow for microeconomic inference
    - For example, welfare analysis using marginal rates of substitution, or willingness to pay
- Recently there is a growing interest in more behavioral models
  - Random regret minimization (Chorus et al., 2014)
  - Attribute-non-attendance (Scarpa et al., 2012)
  - Loss aversion (De Palma et al., 2008)
- Other heuristics are rarely investigated, as there is no modelling framework available

Satisficing

- Satisficing is a heuristics in which individual chooses alternative that is ‘*good enough*’
  - Individuals do not necessarily maximize utility
  - They make decision based on some aspiration level of the objective function
- Information about all alternatives is not readily available
  - Discovered sequentially through a search process
  - Search can be costly (e.g. time/cognitive cost)
  - It can still lead to an optimal choice

Satisficing

- In discrete choice modelling literature there were three applications of this heuristic to date
  - Stüttgen, Boatwright and Monroe (2012)
  - Sandorf and Campbell (2018)
  - González-Valdés and de Dios Ortúzar (2018)
- Previous work employs attribute based inference
  - Individual choose first alternative for which all attributes levels meet given criteria
  - Or individuals may have criteria for only one attribute e.g. "*Choose first alternative that is cheaper than X PLN*"

Proposed model

- We propose a novel framework based on random utility model
- We assume that individual's utility from choosing given alternative is additive and includes stochastic component

$$U_{ij} = \mathbf{X}_{ij}\boldsymbol{\beta}_i + \varepsilon_{ij}$$

- We also assume that individuals have '*satisficing threshold*', ST_i , which describes their aspiration level for utility
    - In the sense, we built upon previous work on choice set formation

Proposed model

- Individual chooses first alternative for which utility exceeds satisficing threshold

	Alternative 1	Alternative 2	Alternative 3
Attribute 1	1	0	1
Attribute 2	2	3	1
Attribute 3	0	0	2

Proposed model

- Individual chooses first alternative for which utility exceeds satisficing threshold

	Alternative 1	Alternative 2	Alternative 3
Attribute 1	1	0	1
Attribute 2	2	3	1
Attribute 3	0	0	2

$$U_{i1} < ST_i$$

Proposed model

- Individual chooses first alternative for which utility exceeds satisficing threshold

	Alternative 1	Alternative 2	Alternative 3
Attribute 1	1	0	1
Attribute 2	2	3	1
Attribute 3	0	0	2

$U_{i1} < ST_i$ $\quad$ $\boxed{U_{i2} > ST_i}$

Proposed model

- Individual chooses first alternative for which utility exceeds satisficing threshold

	Alternative 1	Alternative 2	Alternative 3
Attribute 1	1	0	1
Attribute 2	2	3	1
Attribute 3	0	0	2

$U_{i1} < ST_i$ $\quad$ $U_{i2} > ST_i$ $\quad$ **Choice**

Proposed model

- If none of the utilities exceed satisficing threshold, we assume that individual chooses the one with the highest utility

	Alternative 1	Alternative 2	Alternative 3
Attribute 1	1	0	1
Attribute 2	2	3	1
Attribute 3	0	0	2

Choice → $U_{i1} < ST_i$ $U_{i2} < ST_i$ $U_{i3} < ST_i$

If additionally: $U_{i1} > U_{i2} \wedge U_{i1} > U_{i3}$

Proposed model

- The conditional likelihood for the choice of alternative *j* becomes then

$$P\left(j \mid \boldsymbol{\beta}_i, ST_i\right) = \prod_{k=1}^{j-1} \exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\left(1 - \exp\left(-\exp\left(\mathbf{X}_{ij}\boldsymbol{\beta}_i - ST_i\right)\right)\right) +$$

$$+ \prod_{k=1}^{K}\left(\exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\right)\frac{\exp(\mathbf{X}_{ij}\boldsymbol{\beta}_i)}{\sum \exp(\mathbf{X}_{ik}\boldsymbol{\beta}_i)}$$

Proposed model

- The conditional likelihood for the choice of alternative *j* becomes then

$$P\left(j \mid \boldsymbol{\beta}_i, ST_i\right) = \boxed{\prod_{k=1}^{j-1} \exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)} \left(1 - \exp\left(-\exp\left(\mathbf{X}_{ij}\boldsymbol{\beta}_i - ST_i\right)\right)\right) +$$

$$+ \prod_{k=1}^{K} \left(\exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\right) \frac{\exp(\mathbf{X}_{ij}\boldsymbol{\beta}_i)}{\sum \exp(\mathbf{X}_{ik}\boldsymbol{\beta}_i)}$$

Probability that previous alternatives do not exceed the threshold

Proposed model

- The conditional likelihood for the choice of alternative *j* becomes then

$$P\left(j \mid \boldsymbol{\beta}_i, ST_i\right) = \prod_{k=1}^{j-1} \exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right) \boxed{\left(1 - \exp\left(-\exp\left(\mathbf{X}_{ij}\boldsymbol{\beta}_i - ST_i\right)\right)\right)} +$$

$$+ \prod_{k=1}^{K} \left(\exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\right) \frac{\exp(\mathbf{X}_{ij}\boldsymbol{\beta}_i)}{\sum \exp(\mathbf{X}_{ik}\boldsymbol{\beta}_i)}$$

Probability that alternative *j* does exceed the threshold

Proposed model

- The conditional likelihood for the choice of alternative *j* becomes then

$$P\left(j \mid \boldsymbol{\beta}_i, ST_i\right) = \prod_{k=1}^{j-1} \exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\left(1 - \exp\left(-\exp\left(\mathbf{X}_{ij}\boldsymbol{\beta}_i - ST_i\right)\right)\right) +$$

$$+ \boxed{\prod_{k=1}^{K}\left(\exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\right)} \frac{\exp(\mathbf{X}_{ij}\boldsymbol{\beta}_i)}{\sum \exp(\mathbf{X}_{ik}\boldsymbol{\beta}_i)}$$

Probability that none of the alternatives exceed the threshold

Proposed model

- The conditional likelihood for the choice of alternative *j* becomes then

$$P\left(j \mid \boldsymbol{\beta}_i, ST_i \right) = \prod_{k=1}^{j-1} \exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\left(1-\exp\left(-\exp\left(\mathbf{X}_{ij}\boldsymbol{\beta}_i - ST_i\right)\right)\right)+$$

$$+\prod_{k=1}^{K}\left(\exp\left(-\exp\left(\mathbf{X}_{ik}\boldsymbol{\beta}_i - ST_i\right)\right)\right)\boxed{\frac{\exp(\mathbf{X}_{ij}\boldsymbol{\beta}_i)}{\sum \exp(\mathbf{X}_{ik}\boldsymbol{\beta}_i)}}$$

Probability that alternative *j* maximizes utility

Proposed model

- Preference heterogeneity can be easily incorporated
  - Similarly as in mixed logit
    - In current application we assume that all parameters are random and correlated (normally or log-normally distributed)
    - Satisficing threshold is also random and follows normal distribution
- Model is extended to incorporate stochastic satisficing
- If satisficing threshold is very large then model becomes a regular random utility model
  - Straightforward to test for satisficing behavior in the data
- Marginal rates of substitution can be easily calculated as ratio of parameters

Data

- Stated preferences are widely used to measure the value of non-market goods
  - In transportation, marketing, health, culture, environmental economics, …
  - Based on surveys
- In recent years, Discrete Choice Experiments became a leading method in the field
  - Respondents are asked to choose between several alternatives of public policy described by various attributes (monetary and non-monetary)
- Many advantages:
  - Capture use and passive-use values
  - Go beyond the scope of the existing data
- But also important disadvantages:
  - Not based on market behavior
  - Hypothetical

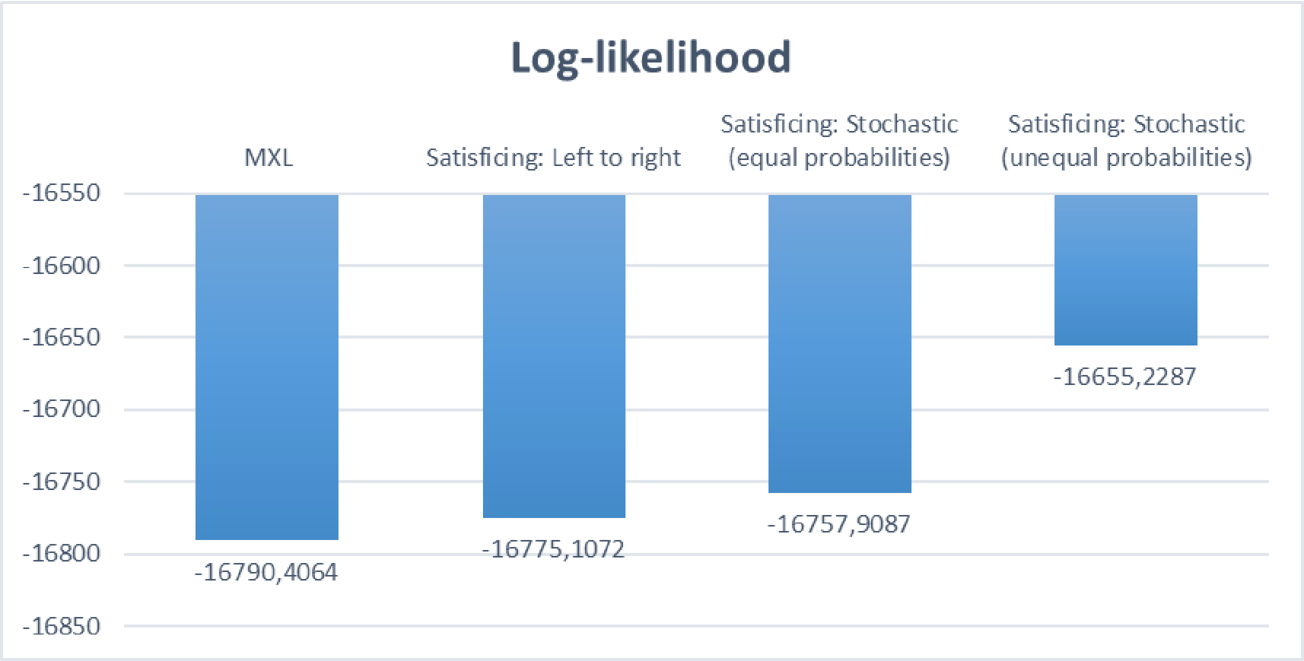
Data

- Discrete Choice Experiment conducted on representative sample of 1001 Poles
- Objective of the study was to analyze preferences towards different programs of forest management in Poland
- 4 attributes
  - Passive protection of most ecologically valuable forests (Levels: 50% (SQ), 75%, 100%)
  - Amount of litter (Levels: No change, 50% reduction, 90% reduction)
  - Infrastructure for tourists (Levels: No change, Infrastructure in 50% additional forests, Infrastructure in 100% additional forests)
  - Cost (Levels: 0, 10, 25, 50, 100 PLN annually)
- 4 alternatives (including *status quo*), 26 choice tasks

Choice task example

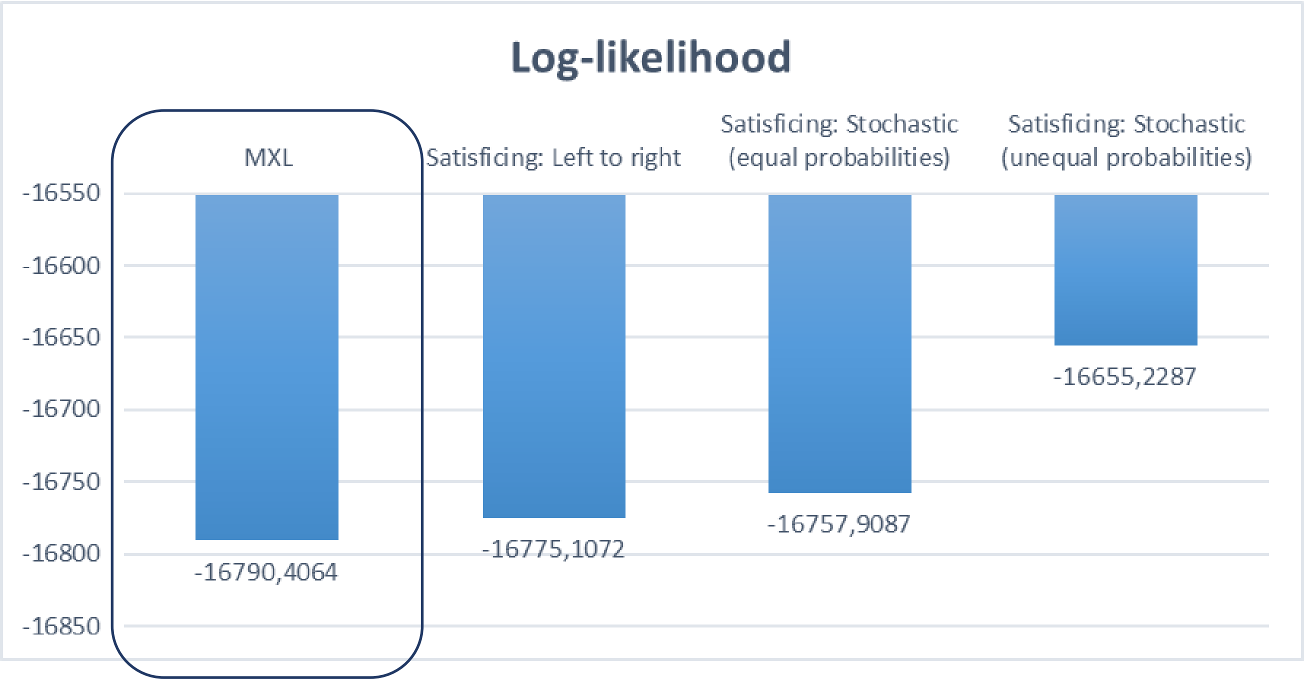
	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Protection of ecologically valuable forests	**Status quo** Passive protection of **50%** of the most ecologically valuable forests (1.5% of all forests)	**Status quo** Passive protection of **50%** of the most ecologically valuable forests (1.5% of all forests)	**Status quo** Passive protection of **50%** of the most ecologically valuable forests (1.5% of all forests)	**Substantial improvement** Passive protection of 100% of the most ecologically valuable forests (3% of all forests, 100% increase)
Litter in forests	**Status quo** No change in the amount of litter in the forests	**Partial improvement** Decrease the amount of litter in the forests by half (50% reduction)	**Status quo** No change in the amount of litter in the forests	**Partial improvement** Decrease the amount of litter in the forests by half (50% reduction)
Infrastructure	**Status quo** No change in tourist infrastructure	**Status quo** No change in tourist infrastructure	**Partial improvement** Appropriate tourist infrastructure in an additional 50% of the forests (50% increase)	**Substantial improvement** Appropriate tourist infrastructure available in twice as many forests (100% increase)
Cost	0 PLN	10 PLN	25 PLN	100 PLN

Results



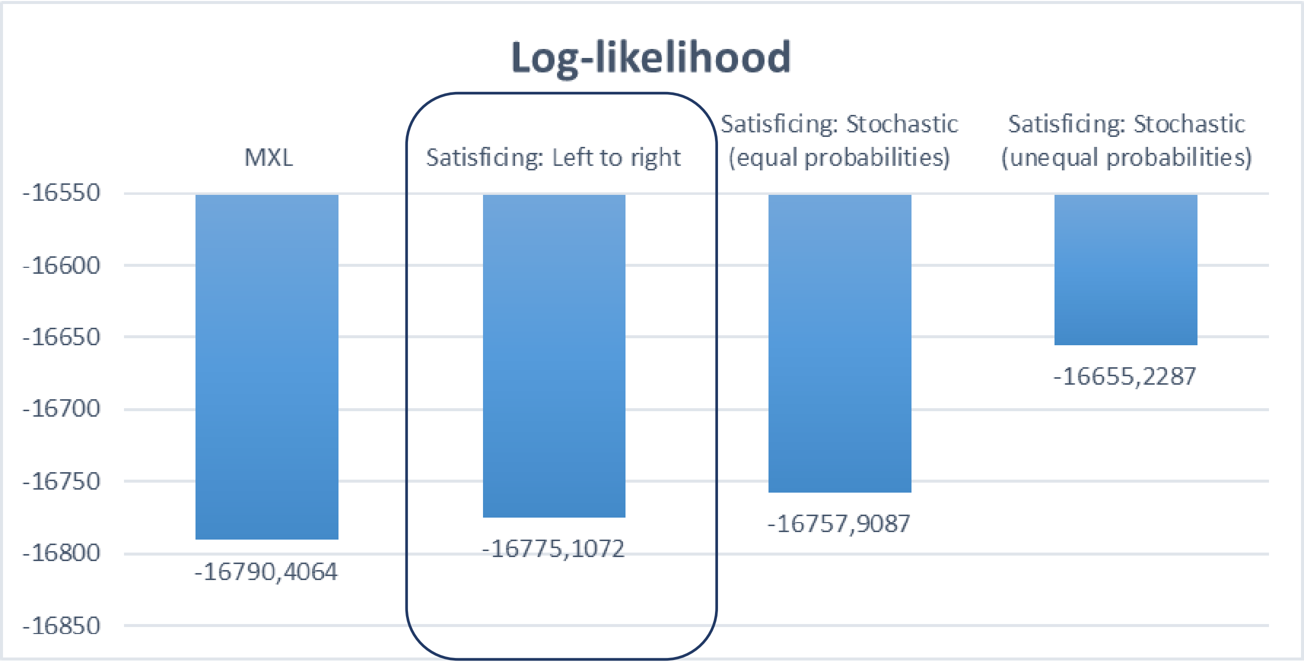
- We compare 4 models:

Results



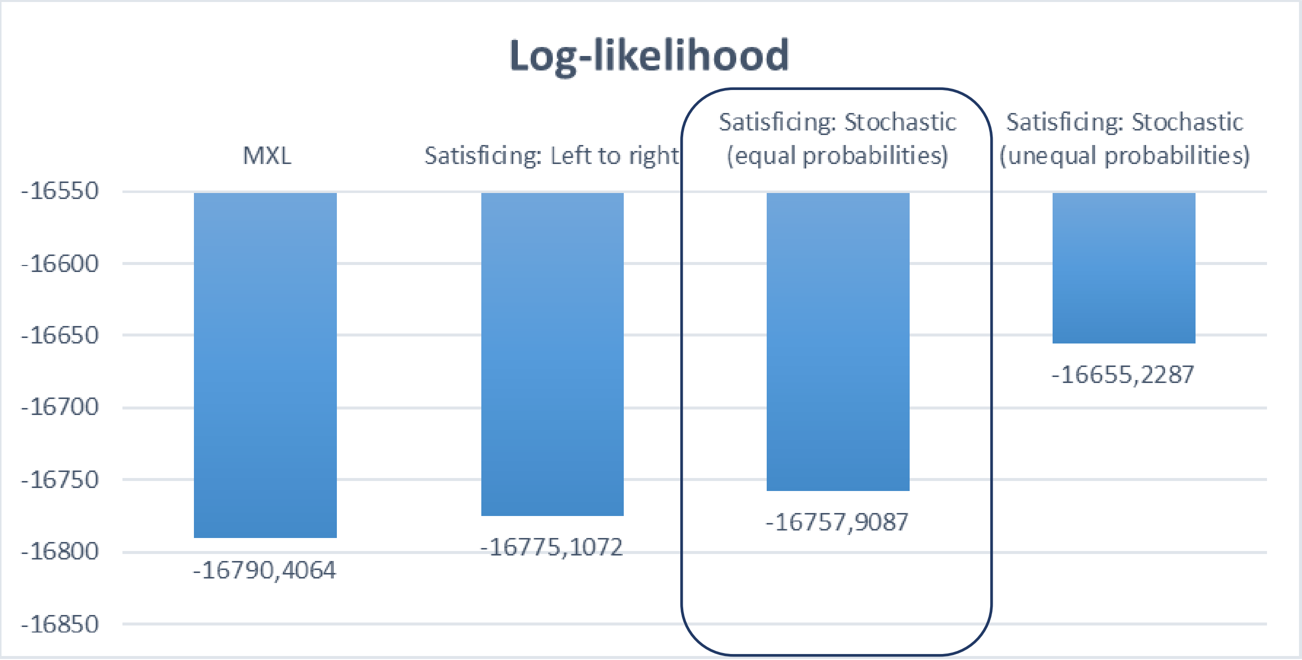
- We compare 4 models:
  - Basic Mixed Logit (MXL)
    - Random utility
    - No satisficing

Results



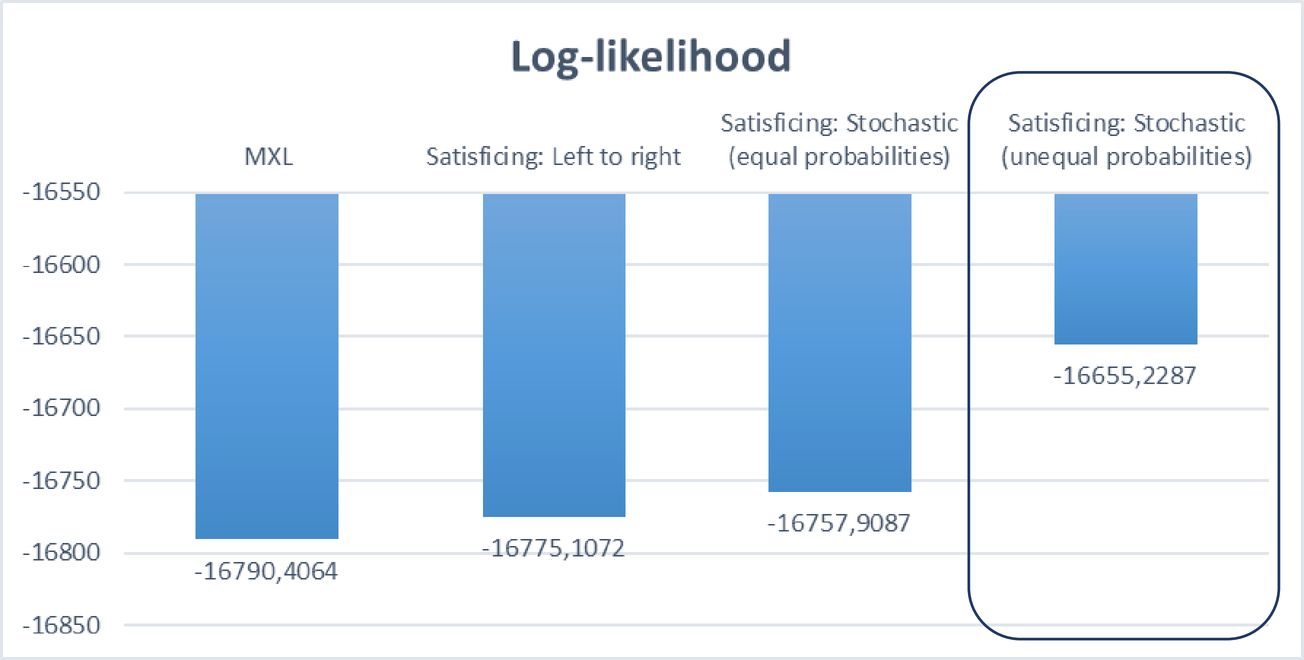
- We compare 4 models:
  - Satisficing Model
    - Order in which individuals evaluate alternatives is fixed
    - It is assumed that individuals go from left to right

Results



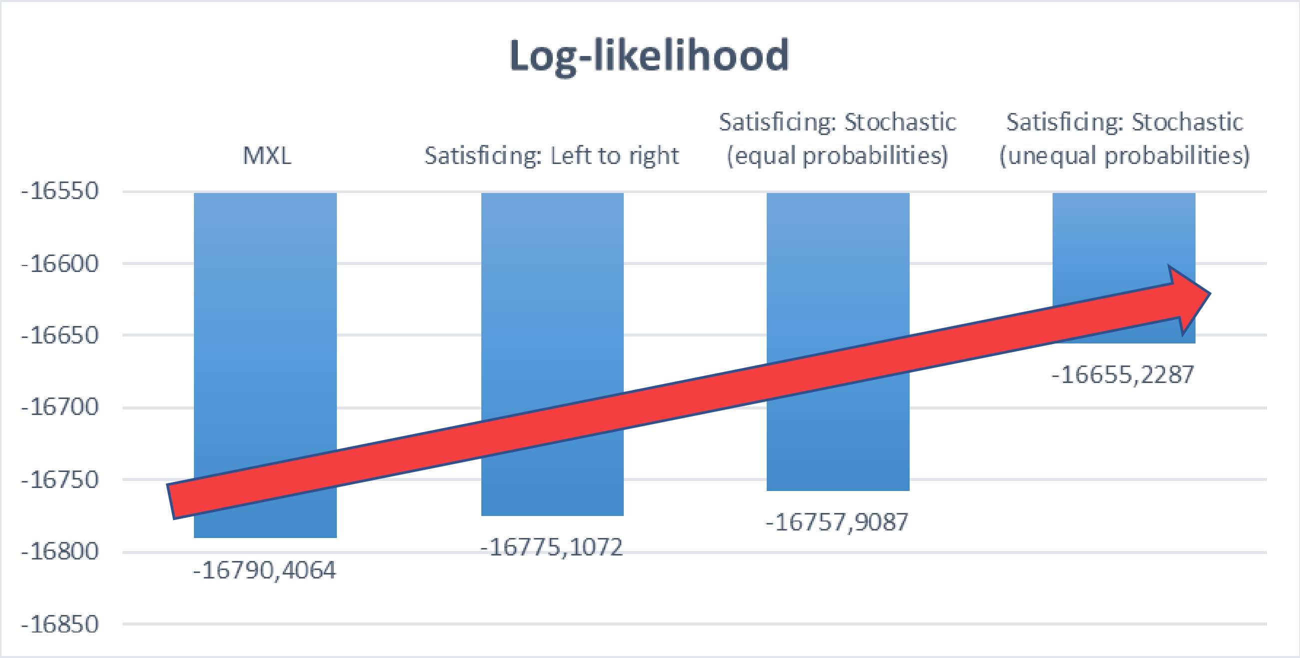
- We compare 4 models:
  - Stochastic Satisficing Model
    - Order in which individuals evaluate alternative is random
      - From the researcher perspective
    - Every order possible with the same probability

Results



- We compare 4 models:
  - Stochastic Satisficing Model
    - Order in which individuals evaluate alternative is random
      - From the researcher perspective
    - Different orders can have different probabilities

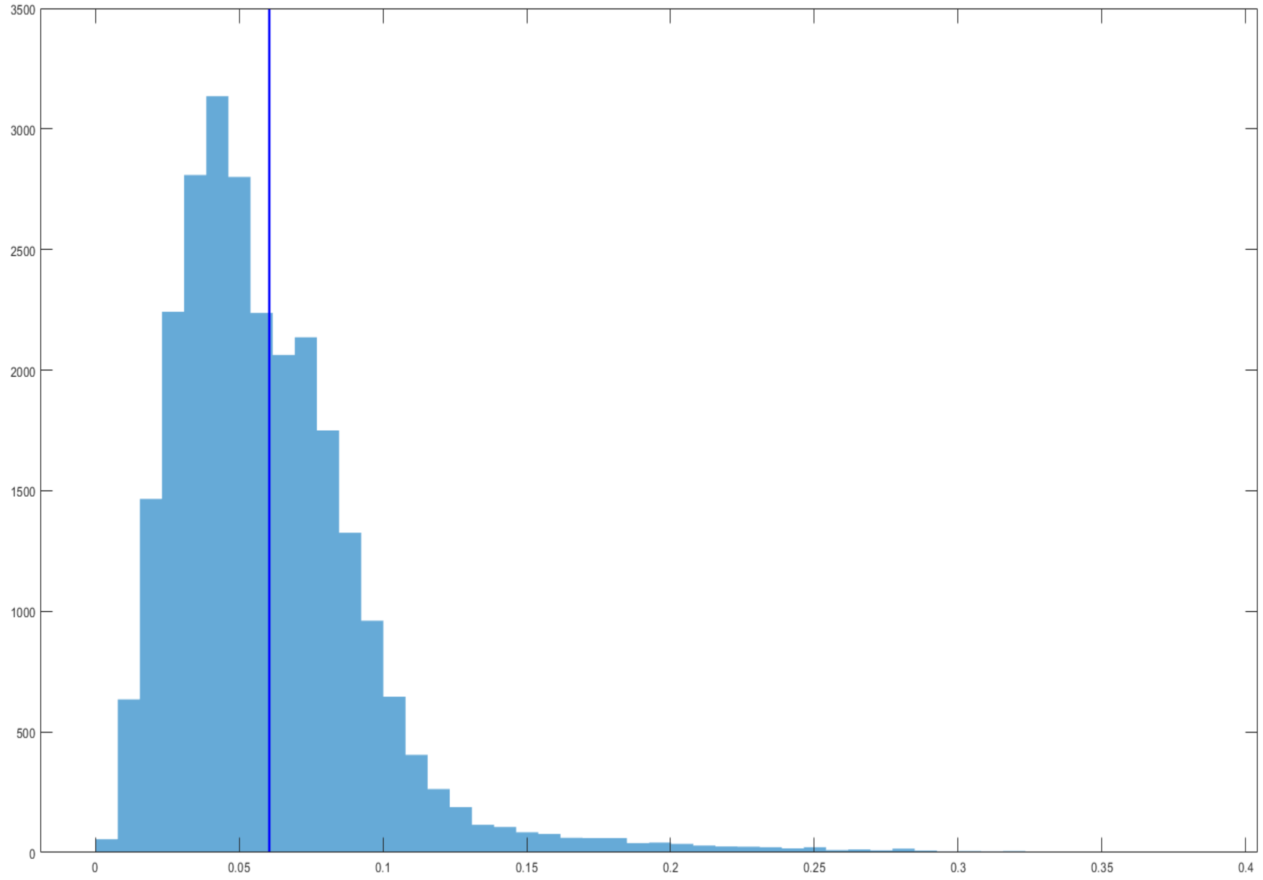
Results



- We compare 4 models:
  - Log-likelihood is increasing significantly
    - MXL is nested in all Satisficing Models
  - 4th model provides the best fit to the data
  - The same conclusion when using AIC or BIC for the comparison

Results

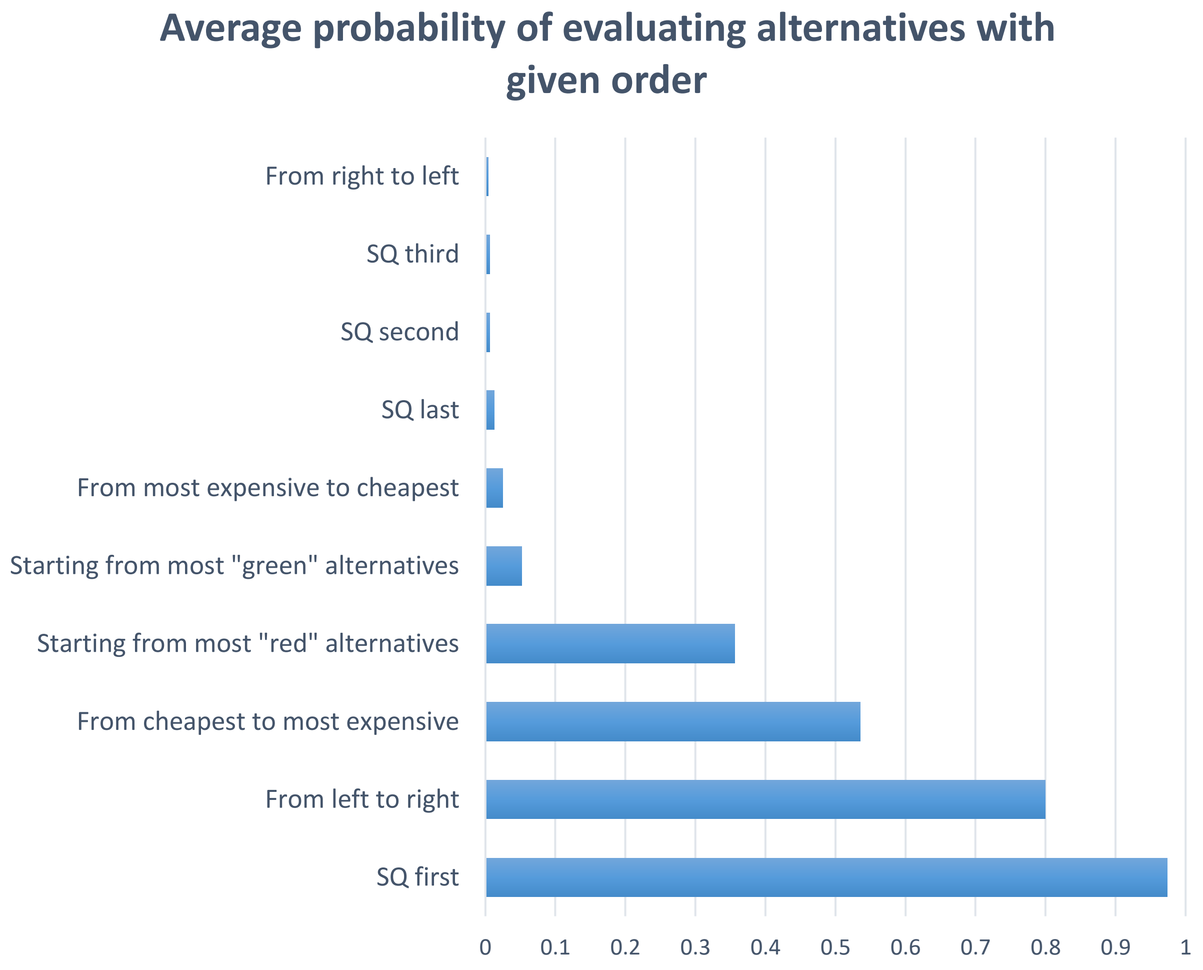
- Share of the probability of choosing a given alternative that is explained by satisficing behavior
  - Ranges from 0% to 35%
  - On average 6%
  - Random utility model seems to explain bigger share of behavior than satisficing



Stochastic Satisficing model : Unequal probabilities

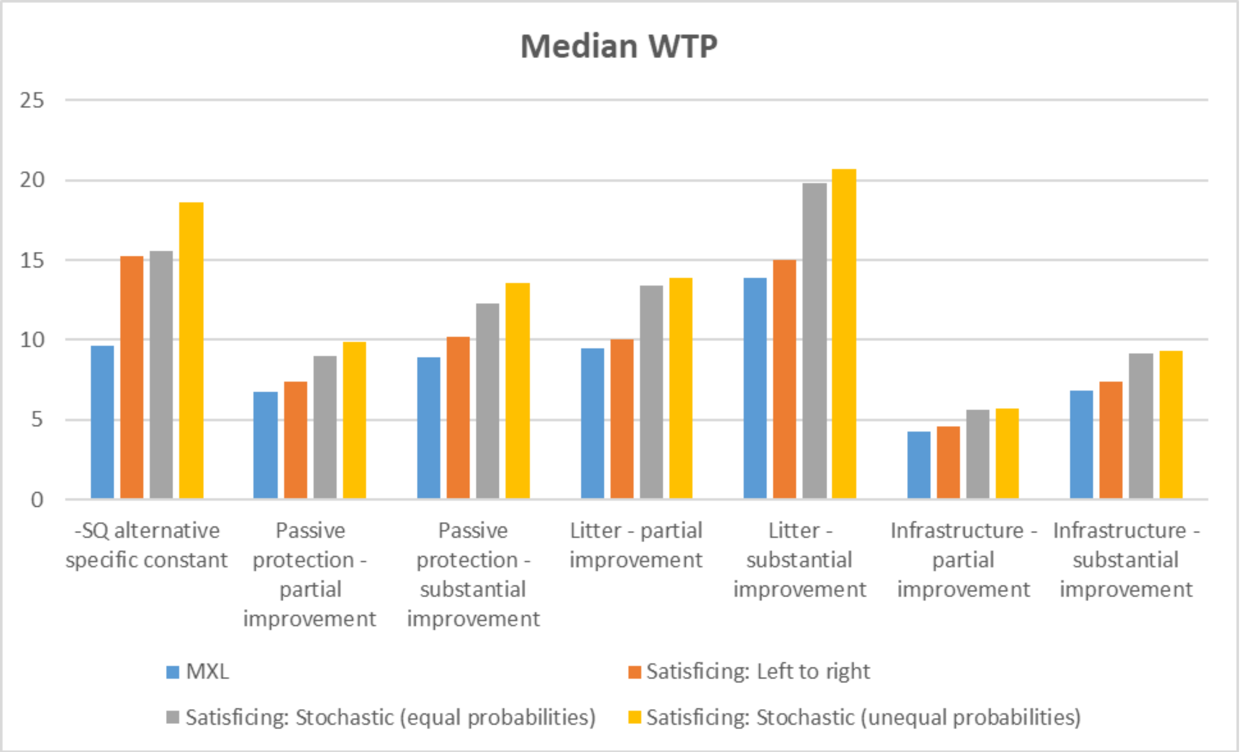
Results

- There is a significant decision process heterogeneity with Stochastic Satisficing
    - Almost all individuals start with SQ
    - Around 80% go from left to right
    - Around 50% go from the cheapest to the most expensive



Results

- Obtaining Willigness To Pay values is usually the main objective of SP studies
- We find significant differences in median WTP estimates when using Stochastic Satisficing model
  - Model with deterministic order provides similar estimates to the regular MXL



Conclusions

- The proposed model leads to a significant improvement in a fit to the data
  - Nevertheless, satisficing seems to explain lower share of choice probabilities than a random utility model
- Satisficing behavior affects WTP estimates
    - Especially when Stochastic Satisficing is taken into account
    - Behavior that is not based on the random utility paradigm matters for stated prefence methods
- Future work
  - Analyzing more datasets (based also on the revealed preferences)
  - Using eye-tracking data

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