

Online Supplement to
 “From descriptive indices of intransitivity to quantitative
 assessments: A commentary on Kalenscher et al. 2010.”

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Random preference model of lexicographic semiorders (RPLS):

Let \mathcal{LSO} be the (finite) collection of lexicographic semiorders, let P_{\succ} denote the probability of $\succ \in \mathcal{LSO}$. The binary choice probability, $p(x, y)$ that a decision maker chooses x when offered the choice between x and y is

$$p(x, y) = \sum_{\substack{\text{preference states } \succ \in \mathcal{LSO} \\ \text{in which } x \succ y}} P_{\succ} + \frac{1}{2} \sum_{\substack{\text{preference states } \succ \in \mathcal{LSO} \\ \text{in which } x \not\succeq y \text{ and } y \not\succeq x}} P_{\succ}. \quad (1)$$

Lexicographic semiorder error model (LSE):

Let $\succ \in \mathcal{LSO}$ be the (unknown) fixed lexicographic semiorder. The binary choice probability, $p(x, y)$ that a decision maker chooses x when offered the choice between x and y is

$$p(x, y) \begin{cases} \in [\frac{1}{2}, 1] & \text{if } x \succ y, \\ \in [\frac{1}{4}, \frac{3}{4}] & \text{if } x \not\succeq y \text{ and } y \not\succeq x, \\ \in [0, \frac{1}{2}] & \text{if } y \succ x. \end{cases} \quad (2)$$

The LSE model forms a complicated non-disjoint union of convex polytopes. While computing its Bayes factor is not computationally expensive, computing a frequentist p-value would require very extensive computation, hence we omit it.

Table 1 provides the frequentist p-values for the random preference model of transitivity (RPT), weak stochastic transitivity (WST), and the random preference model of lexicographic semiorders (RPLS).

Table 1: Reanalysis of Kalenscher et al.’s data. For each of 30 participants, we report the Kalenscher et al. degree of intransitivity score (K. Index) and p-values for goodness-of-fit tests of RPT, WST and RPLS. We boldface K. Index values (> 0.3) that fail to support transitivity. We italicize p-values less than .05, indicating lack of fit for that model. Entries with a “✓” correspond to choice data that perfectly satisfies the constraints of that model, hence a perfect fit.

Participant	K. Index	RPT	WST	RPLS
1	.21	✓	✓	.41
2	.36	<i><.01</i>	<i>.03</i>	<i><.01</i>
3	.605	<i><.01</i>	<i><.01</i>	.43
4	.065	0.12	✓	.22
5	.30	<i><.01</i>	<i><.01</i>	.05
6	.36	.81	.48	<i><.01</i>
7	.31	<i>.02</i>	.45	<i>.03</i>
8	.005	✓	✓	.99
9	.26	✓	.56	.62
10	.41	.27	.20	<i><.01</i>
11	.26	.22	✓	<i>.01</i>
12	.15	✓	✓	.32
13	.43	<i><.01</i>	<i><0.01</i>	.05
14	.050	.29	✓	.39
15	.33	<i><.01</i>	<i><.01</i>	.05
16	.37	<i><.01</i>	<i><.01</i>	<i>.02</i>
17	.42	.55	.72	<i><.01</i>
18	.050	.95	✓	.69
19	.39	.30	.44	<i><.01</i>
20	.39	.22	.36	<i>.03</i>
21	.43	.46	.48	<i><.01</i>
22	.36	<i><.01</i>	<i><.01</i>	.99
23	.20	<i><.01</i>	.66	<i><.01</i>
24	.42	✓	.69	<i>.02</i>
25	.40	.46	.05	.17
26	.29	✓	✓	<i>.03</i>
27	.35	✓	✓	<i><.01</i>
28	.33	.73	.44	<i>.04</i>
29	.25	.07	✓	<i><.01</i>
30	.0067	✓	✓	.69