Online Appendix of
"The Rich Domain of Ambiguity Explored"

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OA.1 References comparing parametric fittings of nonexpected utility

We list some references on decision under risk that use nonexpected utility to fit data, and that compare fits of different parametric families. Our search was done using the annotated bibliography at http://people.few.eur.nl/wakker/refs/webrfrncs.docx of March 16, 2015, using various key words, and choosing the references for which the annotations mentioned the described parametric fitting. The list obviously cannot be complete and cannot even be close to that. It only illustrates that there have been many such studies.

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OA.2 Comparing two orders

We partially randomized the order of presentation of the treatments by using two different orderings: week, basic, year, health, kid; and a partly reversed ordering: health, year, basic, week, kid. Mann-Whitney U-tests are used to compare the matching probabilities derived from these two orders, and the corresponding *p*-values are reported in Table OA.1. The weak and health treatments, whose ranks change the most across these two orders, are not affected by any of the matching probabilities. Other treatments are mostly not affected. Thus, we pool the matching probabilities for all our analyses.

TABLE OA.1. Comparison of matching probabilities between two orderings: Mann-Whitney U tests *p*-values

a-neutral probability	basic	week	year	kid	health
0.1	0.52	0.64	0.35	0.24	0.32
0.3	0.82	0.49	0.37	0.07	0.55
0.5	0.11	0.87	0.05	0.06	0.94
0.7	0.56	0.52	0.46	0.71	0.67
0.9	0.18	0.74	0.35	0.86	0.15

OA.3 Visualizing matching probabilities per a-neutral probability and across treatments

The scatter plots in Figure OA.2 graph matching probabilities of treatments against those of the basic treatment. Each dot represents one subject. The 45-degree line is also shown, together with horizontal and vertical lines indicating a-neutral probability levels.

FIGURE OA.2. Matching probabilities per a-neutral probability and across treatments

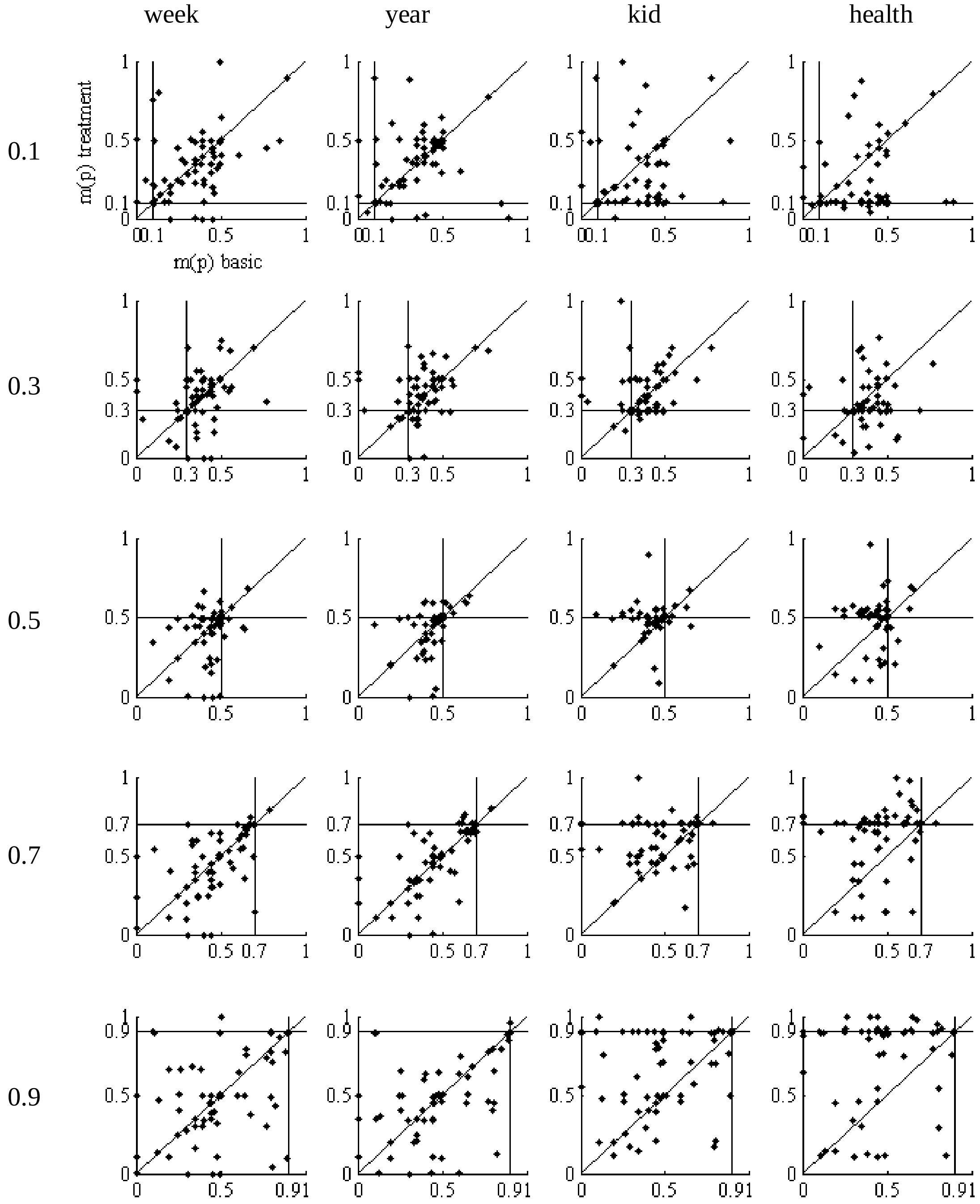


Table OA.2 reports Spearman's rank correlation coefficients of event-dependent ambiguity aversion index *AAj* between the different treatments and basic treatment. The week and year treatments are highly correlated with the basic treatment, while the kid and health treatments are less so.

Table OA.2. Correlation of AAj with basic treatment

a-neutral probability	week	year	kid	health
0.1	0.42^{***}	0.37^{***}	0.21^{*}	0.18
0.3	0.38^{***}	0.39^{***}	0.31^{**}	0.21^{*}
0.5	0.38^{***}	0.59^{***}	0.19	0.02
0.7	0.62^{***}	0.75^{***}	0.24^{**}	0.26^{**}
0.9	0.33^{***}	0.52^{***}	0.24^{*}	0.20

$^{***}\,p \leq 0.01$; $^{**}\,p \leq 0.05$; $^{*}\,p \leq 0.10$

OA.4 Individual indexes b and a

We also extracted the two indexes b and a for every subject per treatment using linear least squares estimations, under the constraint of monotonicity $s \geq 0$. Table OA.3 displays the median of these indexes. Comparing across treatments individually, changes of outcomes do not affect the indexes, which are the same for the basic, week, and year treatments (Wilcoxon signed rank tests: $p > 0.37$ for b; $p > 0.35$ for a), as also confirmed by Friedman's test ($p = 0.76$ for b; $p = 0.89$ for a). Changing the source of uncertainty, the kid treatment gives lower ambiguity aversion (one-sided test: $p < 0.01$) and much better sensitivity ($p < 0.001$) than the basic treatment. The health treatment has yet more sensitivity than the kid treatment ($p < 0.001$), but the same level of ambiguity aversion ($p = 0.13$). Thus, the individual analysis confirms the results of the overall analysis.

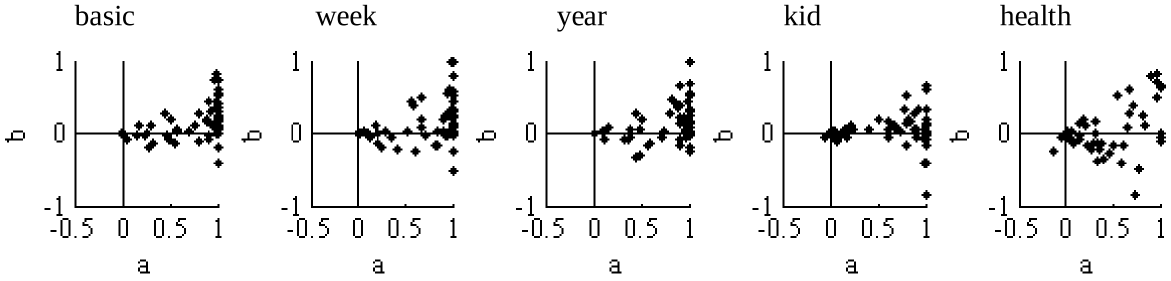
TABLE OA.3. Median individual indexes b and a across treatments

	basic	week	year	kid	health
ambiguity aversion index b	0.11^{***}	0.04^{***}	0.05^{***}	0.01^{**}	-0.01
a-insensitivity index a	0.97^{***}	0.96^{***}	0.97^{***}	0.65^{***}	0.20^{***}

$^{***}\,p \leq 0.01$; $^{**}\,p \leq 0.05$; $^{*}\,p \leq 0.10$

For the empirical joint distribution of the two indexes, see the scatter plots displayed in Figure OA.3. Each dot is one subject. A larger a means more a-insensitivity, where 0 refers to ambiguity neutrality. A larger b means more ambiguity averse, where 0 again refers to ambiguity neutrality.

FIGURE OA.3. Empirical joint distribution of individual indexes b and a



basic week year kid health

OA.5 Parametric version of principal component analysis of the ambiguity attitudes

The field of ambiguity is still in an early stage and the indexes used in this paper are relatively new. Hence an exploratory technique, open to many components, to find the best ones, is still useful. We present such an analysis. Table OA.4 shows the results of a principal component analysis of the event-dependent ambiguity aversion indexes AA_j, j = 1, 3, 5, 7, 9, for each treatment.[1] Dimmock, Kouwenberg, & Wakker (2016) used a similar analysis. A parameter-free analysis is in the next section. For all the treatments, the first two components together account for more than 83% of the variance in the decisions of the subjects. In the basic, week, year, and health treatments, the first component is highly correlated with ambiguity aversion index b and the second component with a-insensitivity index a. The kid treatment, however, reverses the explanatory power of the indexes: a-insensitivity is more dominant than ambiguity aversion. This may be because there is less variation in ambiguity aversion in the kid treatment but less variation in a-insensitivity in the other treatments. These results confirm that indexes a and b are primary components in ambiguity attitudes, capturing most of the variance. This finding confirms early psychological theories (Hogarth & Einhorn 1990).

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[1] The indexes are the raw data (matching probabilities) minus a constant and, hence, are equivalent to raw data.

TABLE OA.4. Principal component analysis of event-dependent ambiguity aversion indexes

Variable		loadings on first two components									
		basic		week		year		kid		health	
		1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
AA_1		0.14	0.83	0.18	0.86	0.14	0.86	-0.53	0.65	0.19	0.77
AA_3		0.18	0.49	0.31	0.37	0.22	0.42	-0.25	0.43	0.19	0.46
AA_5		0.23	0.05	0.33	0.10	0.32	0.11	0.05	0.28	0.34	0.22
AA_7		0.54	-0.03	0.52	-0.14	0.55	-0.11	0.29	0.34	0.52	-0.04
AA_9		0.78	-0.25	0.71	-0.32	0.72	-0.26	0.76	0.44	0.73	-0.39
eigenvalue of the component		0.10	0.05	0.13	0.05	0.11	0.05	0.09	0.06	0.13	0.06
proportion of variance explained (%)		60.32	28.84	61.96	23.49	56.23	27.76	54.12	34.61	62.63	27.71
correlation coefficient	a	0.66***	-0.63***	0.59***	-0.69***	0.62***	-0.70***	0.98***	-0.03	0.40***	-0.80***
	b	0.92***	0.22*	0.94***	0.18	0.92***	0.27**	0.36***	0.88***	0.89***	0.37***

*** $p \leq 0.01$; ** $p \leq 0.05$; * $p \leq 0.10$

OA.6 Non-parametric version of the principal component analysis

To test whether ambiguity attitudes are best explained by the two components, ambiguity aversion and a-insensitivity, we next report a non-parametric version of the principal component analysis here. Table OA.5 shows the principal component analysis on the tied ranks of the event-dependent ambiguity aversion indexes AAj, $j = 1, 3, 5, 7, 9$, for each treatment. For all the treatments, the first two components together account for more than 79% of the variance in the decisions of the subjects. In the basic treatment, the first component is closely correlated with ambiguity aversion index b and the second component more with a-insensitivity index a than b. The week and year treatments yield similar patterns. In the health treatment, the first component is highly correlated with ambiguity aversion index b and the second component with a-insensitivity index a. The kid treatment, however, reverses the explanatory power of these indexes: a-insensitivity is more dominant than ambiguity aversion. An explanation may be that there is less variation in ambiguity aversion in the kid treatment and less variation in a-insensitivity in the health treatment.

TABLE OA.5. Non-parametric principal component analysis of event-dependent ambiguity aversion indexes

		loadings on first two components									
variable		basic		week		year		kid		health	
		1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
AA_1		0.23	0.68	0.24	0.73	0.27	0.67	-0.49	0.41	0.43	-0.40
AA_3		0.30	0.63	0.42	0.48	0.35	0.57	-0.41	0.52	0.48	-0.38
AA_5		0.53	-0.15	0.50	-0.06	0.52	-0.08	0.25	0.64	0.54	-0.14
AA_7		0.54	-0.25	0.52	-0.33	0.54	-0.34	0.49	0.35	0.43	0.50
AA_9		0.54	-0.25	0.50	-0.34	0.50	-0.32	0.54	0.16	0.33	0.66
eigenvalue of the component		949.71	601.34	997.24	473.22	942.40	510.53	927.20	519.81	1049.95	467.05
proportion of variance explained (%)		51.78	32.79	54.51	25.87	51.48	27.89	51.01	28.60	59.18	26.33
correlation coefficient	a	0.51^{***}	-0.69^{***}	0.40^{***}	-0.74^{***}	0.42^{***}	-0.79^{***}	0.94^{***}	-0.11	0.03	0.86^{***}
	b	0.97^{***}	0.11	0.98^{***}	0.07	0.96^{***}	0.07	0.37^{***}	0.68^{***}	0.92^{***}	0.14

$^{***}\, p \leq 0.01$; $^{**}\, p \leq 0.05$; $^{*}\, p \leq 0.10$

OA.7 Individual parameters

In this Online Appendix we further analyze the parametric families defined in the main text. We add two one-parameter families:

Prelec (1998) One-parameter:

$$\text{Eq. 10 with } \beta = 1. \tag{OA.1}$$

Tversky & Kahneman (1992):

$$m(p) = \frac{p^c}{(p^c+(1-p)^c)^{1/c}} \text{ for } c \geq 0.28. \tag{OA.2}$$

Here c is an (anti-)index of both a-insensitivity and ambiguity aversion.

For each subject per treatment, we observe six matching probabilities for six events corresponding to a-neutral probabilities 0.1, 0.3, 0.5, 0.5, 0.7, and 0.9. We fit parameters for the parametric families based on these six observations using least-squares estimation. Table OA.6 displays the median of these individual parameters ($p \leq 0.01$ in all cases). See §OA.9 for visualizations.

TABLE OA.6. Median individual fitted parameters (significance level by comparison with basic treatment)

parametric family	parameters	basic	week	year	kid	health
neo-additive	c	0.33	0.34	0.36	0.21^{***}	0.06^{***}
	s	0.03	0.05	0.04	0.35^{***}	0.83^{***}
Goldstein & Einhorn	$\alpha^{\downarrow}$	0.03	0.04	0.04	0.29^{***}	0.81^{***}
	$\beta^{\downarrow}$	0.80	0.92	0.91	0.98^{***}	1.02^{***}
Prelec two-parameter	$\alpha^{\downarrow}$	0.02	0.03	0.02	0.25^{***}	0.81^{***}
	β	0.90	0.92	0.84	0.93	0.98
Prelec one-parameter	$\alpha^{\downarrow}$	0.11	0.15	0.14	0.39^{***}	0.87^{***}
Tversky & Kahneman	$c^{\downarrow}$	0.55	0.59	0.59	0.69^{***}	1.00^{***}

$^{***}p \leq 0.01$; $^{**}p \leq 0.05$; $^{*}p \leq 0.10$

$^{\downarrow}$: anti-index

Comparing individual parameters across treatments for Goldstein & Einhorn family, changes of outcomes do not affect the parameters, which are the same for the basic, week, and year treatments (Wilcoxon signed rank tests: $p > 0.24$ for β; $p > 0.42$ for α), as also confirmed by Friedman's test ($p = 0.78$ for β; $p = 0.81$ for α). Changing the source of uncertainty, the kid and health treatments give lower ambiguity aversion (higher β, one-sided tests: $p < 0.01$ and $p < 0.001$ respectively) and better sensitivity (higher α, $p < 0.001$ both) than the basic treatment. The health treatment gives even lower ambiguity aversion ($p < 0.05$) and better sensitivity ($p < 0.001$) than the kid treatment.

For the Prelec two-parameter family, changes of outcomes do not affect the parameters, which are the same for the basic, week, and year treatments (Wilcoxon signed rank tests: $p > 0.48$ for β; $p > 0.49$ for α), as also confirmed by Friedman's test ($p = 0.67$ for β; $p = 0.98$ for α). Changing the source of uncertainty, the kid and health treatments give the same level of ambiguity aversion as the basic treatment (β: $p > 0.44$) and better sensitivity (higher α, $p < 0.001$ both) than the basic treatment. The health treatment gives even better sensitivity than the kid treatment ($p < 0.001$).

For the one-parameter families, changes of outcomes do not affect the parameter α in the Prelec one-parameter family or c in Tversky & Kahneman's family, which are the same for the basic, week, and year treatments (Wilcoxon signed rank tests: $p > 0.54$ for α; $p > 0.15$ for c), as also confirmed by Friedman's test ($p = 0.95$ for α; $p = 0.18$ for c). Changing the source of uncertainty, the kid treatment gives higher α and c than the basic treatment (one-sided tests: $p < 0.001$ for both α and c). The health treatment has yet higher α and c than the kid treatment ($p < 0.001$ for both α and c).

OA.8 Correlations of parameters across treatments

Table OA.7 reports the Spearman's rank correlation coefficients of the parameters in the parametric families for every pair of treatments. Correlations among the basic, week, and year treatments are highly significant, except the ambiguity aversion parameter β in the Prelec two-parameter family.

TABLE OA.7. Correlations of parameters across treatments

Goldstein & Einhorn		$\beta^{\downarrow}$				
		basic	week	year	kid	health
$\alpha^{\downarrow}$	basic		0.50***	0.65***	0.28**	0.24**
	week	0.50***		0.52***	0.26**	0.21*
	year	0.55***	0.30**		0.47***	0.35***
	kid	0.39***	0.31**	0.23*		0.18
	health	-0.01	-0.04	-0.06	0.29**	
Prelec two-parameter		β				
		basic	week	year	kid	health
$\alpha^{\downarrow}$	basic		0.45***	0.60***	0.28**	0.27**
	week	0.43***		0.44***	0.25**	0.25**
	year	0.51***	0.25***		0.37***	0.34***
	kid	0.36***	0.24*	0.11		0.22*
	health	0.12	-0.02	-0.02	0.31**	
		Tversky & Kahneman $c^{\downarrow}$				
		basic	week	year	kid	health
Prelec two-parameter $\alpha^{\downarrow}$	basic		0.22*	0.16	0.29**	0.02
	week	0.45***		0.14	0.19	0.30**
	year	0.60***	0.49***		0.37***	0.06
	kid	0.32***	0.22*	0.16		0.42***
	health	0.24**	0.11	0.19	0.16	

*** $p \leq 0.01$; ** $p \leq 0.05$; * $p \leq 0.10$

$^{\downarrow}$: anti-index

OA.9 Correlations between various ambiguity measures per treatment

Table OA.8 reports the Spearman's rank correlation coefficients of the parameters in the parametric families for each treatment. The parameters resulting from the neo-additive family are our indexes a, b. Goldstein & Einhorn's β and α are anti-indexes of ambiguity aversion and a-insensitivity, respectively. They have almost perfect negative correlations with the aversion and insensitivity parameters b and a, implying that the Goldstein & Einhorn and neo-additive families capture the same components of ambiguity attitudes. In the Prelec two-parameter family, β is an index of ambiguity aversion and α an anti-index of a-insensitivity. Empirically, other than for the kid treatment, the two parameters are well separated and correlations of α with the aversion parameter a are consistent with expectation. For the ambiguity aversion indexes b, β, correlations are less than perfect, especially in the kid treatment. This is possibly because it cannot capture the change of ambiguity aversion, resulting in estimations not significantly different among the treatments. For the one-parameter families of Prelec and Tversky & Kahneman, the correlations with the other parameters are not stable, showing that the one parameter captures different aspects in different treatments.

TABLE OA.8. Correlations between various ambiguity attitude measures per treatment

basic		indexes a, b		Goldstein & Einhorn		Prelec two-parameter		Prelec one-parameter	Tversky & Kahneman
		b	a	$\beta^{\downarrow}$	$\alpha^{\downarrow}$	β	$\alpha^{\downarrow}$	$\alpha^{\downarrow}$	$c^{\downarrow}$
indexes a, b	b		0.45^{***}	-1.00^{***}	-0.42^{***}	0.83^{***}	-0.48^{***}	-0.80^{***}	-0.34^{***}
	a			-0.43^{***}	-0.96^{***}	0.00	-0.92^{***}	-0.80^{***}	-0.47^{***}
Goldstein & Einhorn	$\beta^{\downarrow}$				0.40^{***}	-0.84^{***}	0.46^{***}	0.78^{***}	0.32^{***}
	$\alpha^{\downarrow}$					0.01	0.94^{***}	0.78^{***}	0.43^{***}
Prelec two-parameter	β						-0.05	-0.43^{***}	-0.01
	$\alpha^{\downarrow}$							0.82^{***}	0.50^{***}
Prelec one-parameter	$\alpha^{\downarrow}$								0.52^{***}

week		indexes a, b		Goldstein & Einhorn		Prelec two-parameter		Prelec one-parameter	Tversky & Kahneman
		b	a	$\beta^{\downarrow}$	$\alpha^{\downarrow}$	β	$\alpha^{\downarrow}$	$\alpha^{\downarrow}$	$c^{\downarrow}$
indexes a, b	b		0.39^{***}	-1.00^{***}	-0.28^{**}	0.87^{***}	-0.39^{***}	-0.82^{***}	-0.07
	a			-0.37^{***}	-0.92^{***}	0.02	-0.91^{***}	-0.77^{***}	-0.46^{***}
Goldstein & Einhorn	$\beta^{\downarrow}$				0.26^{**}	-0.88^{***}	0.37^{***}	0.80^{***}	0.06
	$\alpha^{\downarrow}$					0.09	0.93^{***}	0.70^{***}	0.60^{***}
Prelec two-parameter	β						-0.03	-0.51^{***}	0.20
	$\alpha^{\downarrow}$							0.77^{***}	0.54^{***}
Prelec one-parameter	$\alpha^{\downarrow}$								0.32^{***}

year		indexes a, b		Goldstein & Einhorn		Prelec two-parameter		Prelec one-parameter	Tversky & Kahneman
		b	a	$\beta^{\downarrow}$	$\alpha^{\downarrow}$	β	$\alpha^{\downarrow}$	$\alpha^{\downarrow}$	$c^{\downarrow}$
indexes a, b	b		0.35***	-1.00***	-0.34***	0.87***	-0.39***	-0.79***	-0.10
	a			-0.34***	-0.91***	-0.05	-0.91***	-0.72***	-0.36***
Goldstein & Einhorn	$\beta^{\downarrow}$				0.32***	-0.88***	0.38***	0.78***	0.10
	$\alpha^{\downarrow}$					0.07	0.93***	0.70***	0.45***
Prelec two-parameter	β						0.01	-0.47***	0.18
	$\alpha^{\downarrow}$							0.74***	0.48***
Prelec one-parameter	$\alpha^{\downarrow}$								0.26**
kid		indexes a, b		Goldstein & Einhorn		Prelec two-parameter		Prelec one-parameter	Tversky & Kahneman
		b	a	$\beta^{\downarrow}$	$\alpha^{\downarrow}$	β	$\alpha^{\downarrow}$	$\alpha^{\downarrow}$	$c^{\downarrow}$
indexes a, b	b		0.29**	-0.99***	-0.25**	0.49***	-0.31***	-0.55***	-0.38***
	a			-0.26**	-0.98***	-0.51***	-0.98***	-0.91***	-0.70***
Goldstein & Einhorn	$\beta^{\downarrow}$				0.21*	-0.52***	0.29**	0.53***	0.35***
	$\alpha^{\downarrow}$					0.55***	0.98***	0.90***	0.74***
Prelec two-parameter	β						0.48***	0.25**	0.43***
	$\alpha^{\downarrow}$							0.93***	0.77***
Prelec one-parameter	$\alpha^{\downarrow}$								0.75***
health		indexes a, b		Goldstein & Einhorn		Prelec two-parameter		Prelec one-parameter	Tversky & Kahneman
		b	a	$\beta^{\downarrow}$	$\alpha^{\downarrow}$	β	$\alpha^{\downarrow}$	$\alpha^{\downarrow}$	$c^{\downarrow}$
indexes a, b	b		0.15	-0.99***	-0.08	0.92***	-0.19	-0.47***	0.51***
	a			-0.14	-0.95***	-0.07	-0.94***	-0.81***	-0.26**
Goldstein & Einhorn	$\beta^{\downarrow}$				0.07	-0.93***	0.18	0.47***	-0.53***
	$\alpha^{\downarrow}$					0.15	0.98***	0.79***	0.34***
Prelec two-parameter	β						0.05	-0.26**	0.71***
	$\alpha^{\downarrow}$							0.87***	0.30**
Prelec one-parameter	$\alpha^{\downarrow}$								0.12

$^{***}\ p \leq 0.01$; $^{**}\ p \leq 0.05$; $^{*}\ p \leq 0.10$

$^{\downarrow}$: anti-index

OA.10 Fit of parametric families: Bayesian information criterion (BIC)

TABLE OA.9. Fit of parametric families: Bayesian information criterion (BIC)

parametric family	basic	week	year	kid	health
neo-additive	–273.13	–140.71	–193.27	–242.23	–159.25
Goldstein & Einhorn	–272.15	–140.69	–192.66	–240.61	–156.80
Prelec two-parameter	–269.95	–140.08	–191.06	–235.89	–156.09
Prelec one-parameter	–263.87	–140.02	–180.25	–213.48	–154.76
Tversky & Kahneman	–170.78	–73.79	–93.10	–187.31	–153.07

OA.11 Results on parametric fittings with two one-parameter families included

In this Online Appendix we repeat the results of parametric fittings, but now with two one-parameter families defined in Appendix OA.7 added.[2] Table OA.10 shows that the ordering of goodness of fit by Akaike's information criterion (AIC) is, for all treatments: (1) neo-additive; (2) Goldstein & Einhorn; (3) Prelec two-parameter; (4) Prelec one-parameter; (5) Tversky & Kahneman. Because insensitivity plays a more central role for ambiguity than for risk, Prelec's one-parameter family (focusing on insensitivity) fares better in this case than Tversky & Kahneman's.

TABLE OA.10. Fit of parametric families: Akaike's information criterion (AIC)

parametric family	basic	week	year	kid	health
neo-additive	–281.09	–148.67	–201.24	–250.19	–167.21
Goldstein & Einhorn	–280.12	–148.65	–200.63	–248.57	–164.76
Prelec two-parameter	–277.91	–148.04	–199.03	–243.85	–164.06
Prelec one-parameter	–267.86	–144.00	–184.23	–217.46	–158.74
Tversky & Kahneman	–174.76	–77.77	–97.08	–191.29	–157.05

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[2] We thank an editor for recommending removing this analysis from the main text.

TABLE OA.11. Fitted parameters (significance level given by comparison with the basic treatment)

parametric family	parameters	basic	week	year	kid	health
neo-additive	c	0.33	0.32	0.35	0.26^{**}	0.15^{***}
	s	0.19	0.20	0.17	0.45^{***}	0.66^{***}
Goldstein & Einhorn	$\beta^{\downarrow}$	0.74	0.73	0.76	0.92^{***}	0.93^{***}
	$\alpha^{\downarrow}$	0.15	0.15	0.13	0.35^{***}	0.55^{***}
Prelec two-parameter	β	0.91	0.93	0.89	0.86	0.92
	$\alpha^{\downarrow}$	0.14	0.14	0.12	0.35^{***}	0.56^{***}
Prelec one-parameter	$\alpha^{\downarrow}$	0.18	0.18	0.17	0.42^{***}	0.60^{***}
Tversky & Kahneman	$c^{\downarrow}$	0.52	0.51	0.52	0.62^{***}	0.70^{***}

$^{***}\ p \leq 0.01$; $^{**}\ p \leq 0.05$; $^{*}\ p \leq 0.10$

$^{\downarrow}$: anti-index

Table OA.11 reports the fitted parameters of these parametric families (all significant at the 1% level).[3] In addition to what was reported in the main text, comparing between the health and kid treatments, the Prelec one-parameter family also gives a higher α ($p < 0.01$), but Tversky and Kahneman's family gives the same c for the health and kid treatments ($p = 0.13$).

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[3] We also fit these parametric families individually. For medians of those individual parameters, correlations of parameters across treatments, and correlations among parametric families per treatment, see Online Appendix OA.7. They confirm all results reported here.

OA.12 Visualizing matching probabilities per subject and treatment (with individual parameters)

The individual parameters in each panel are listed in the following order:

neo-additive: c s

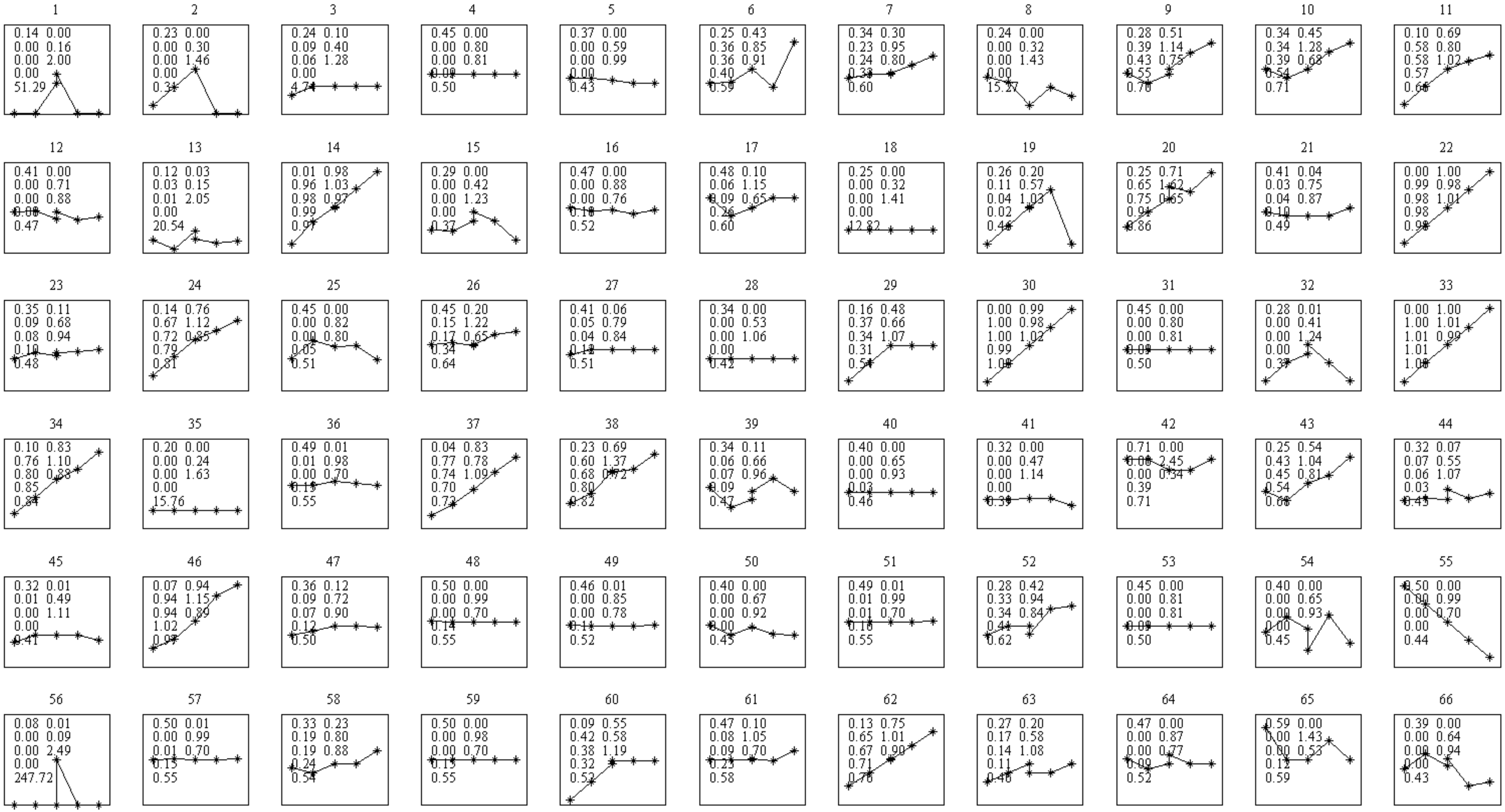
Goldstein & Einhorn: α β

Prelec two-parameter: α β

Prelec one-parameter: α

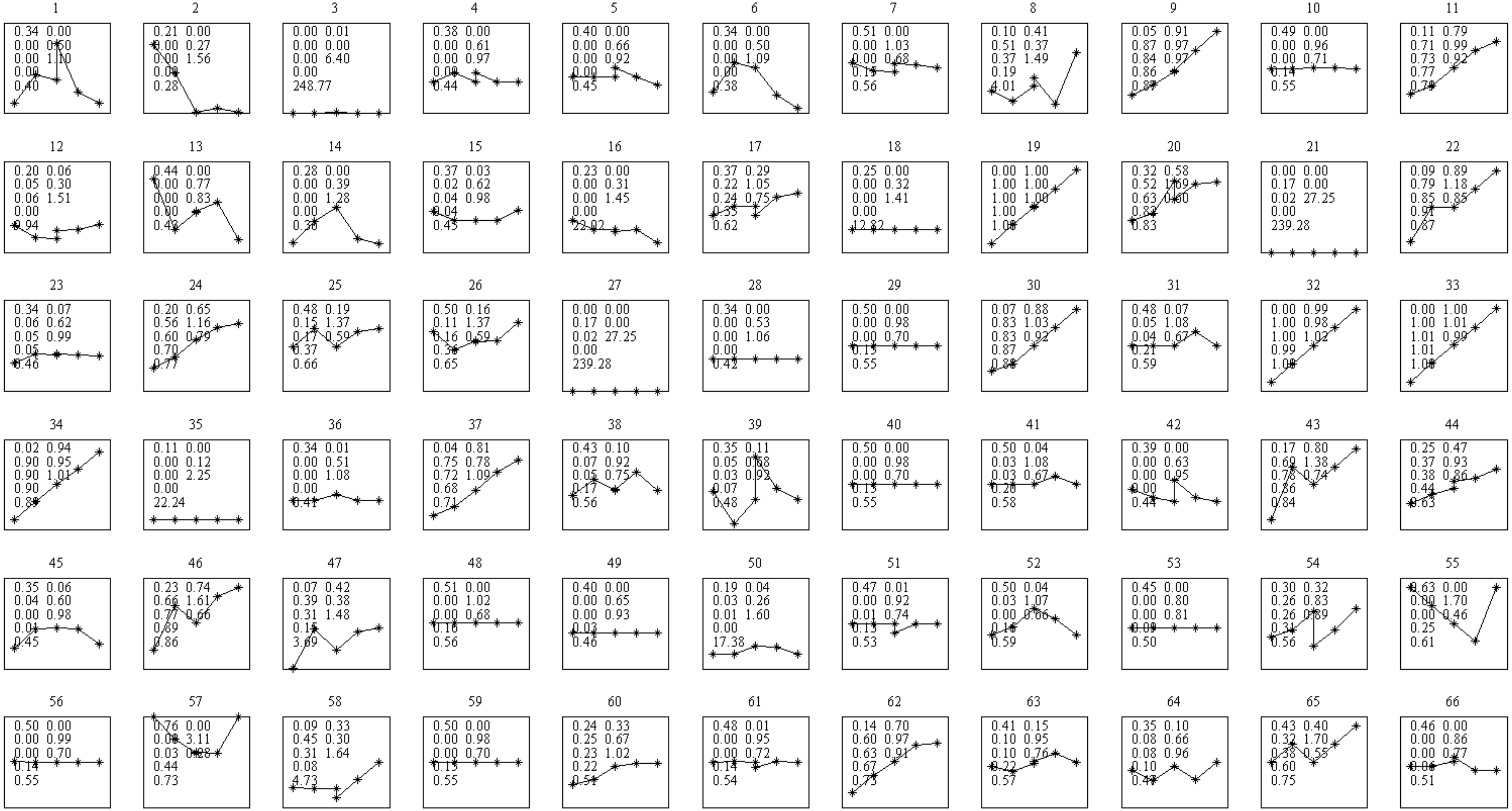
Tversky & Kahneman: c

basic treatment

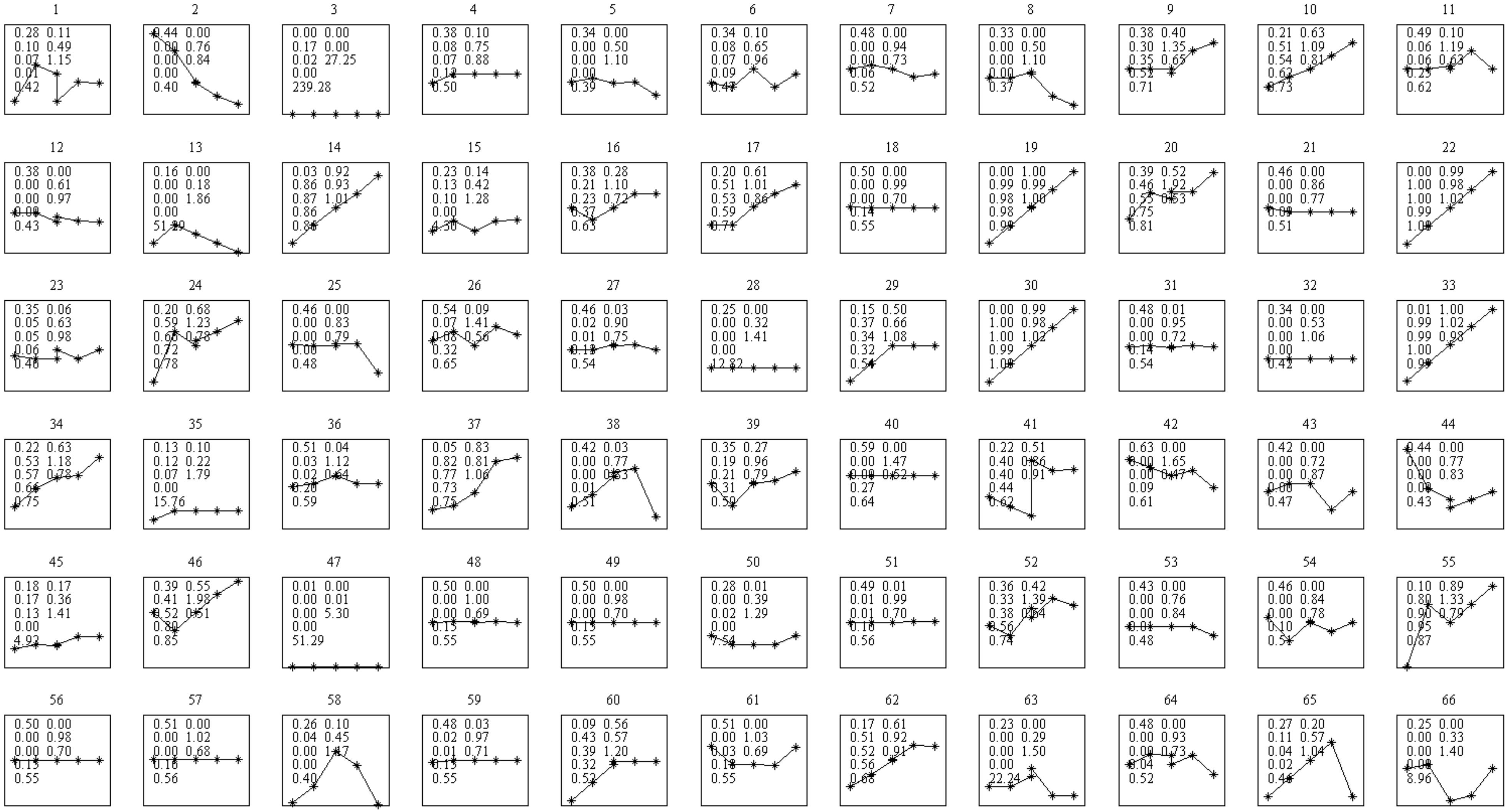


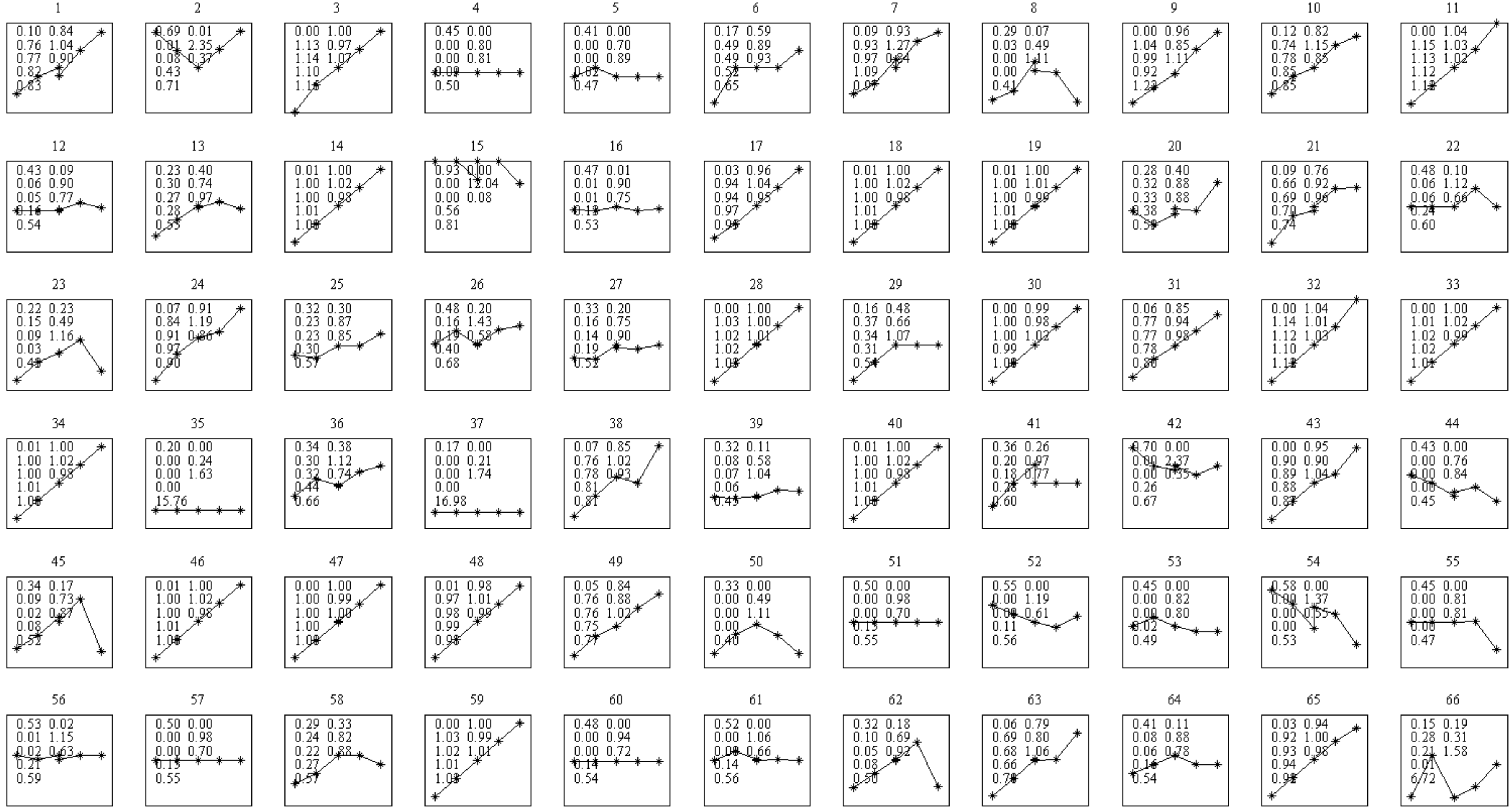
24

week treatment



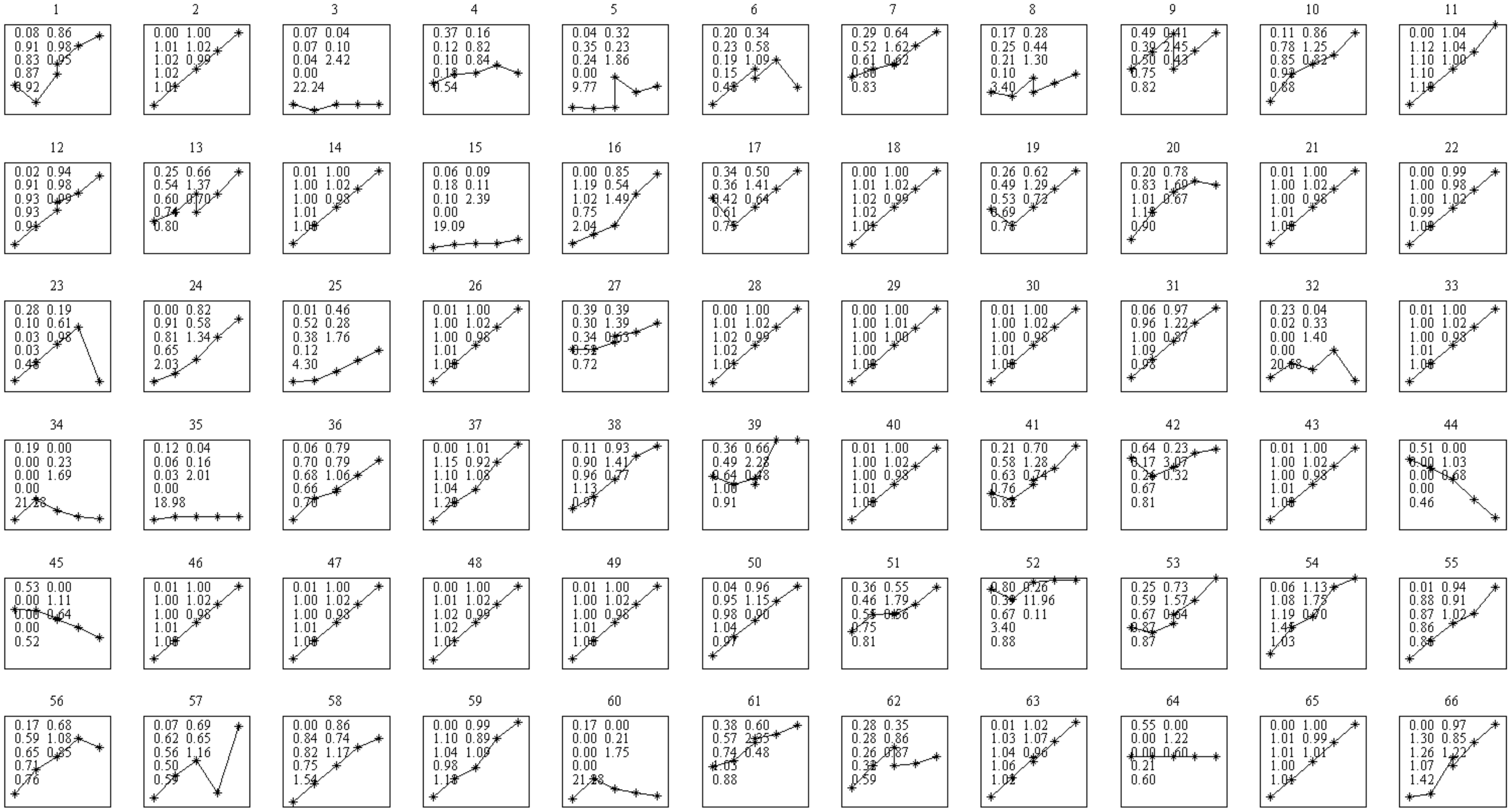
year treatment





kid treatment

health treatment



Additional reference for Online Appendix

Hogarth, Robin M. & Hillel J. Einhorn (1990) "Venture Theory: A Model of Decision Weights," *Management Science* 36, 780–803.