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Research Article

Are Probabilities Overweighted or Underweighted When Rare Outcomes Are Experienced (Rarely)?

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ABSTRACT—*When making decisions involving risky outcomes on the basis of verbal descriptions of the outcomes and their associated probabilities, people behave as if they overweight small probabilities. In contrast, when the same outcomes are instead experienced in a series of samples, people behave as if they underweight small probabilities. We present two experiments showing that the existing explanations of the underweighting observed in decisions from experience are not sufficient to account for the effect. Underweighting was observed when participants experienced representative samples of events, so it cannot be attributed to undersampling of the small probabilities. In addition, earlier samples predicted decisions just as well as later samples did, so underweighting cannot be attributed to recency weighting. Finally, frequency judgments were accurate, so underweighting cannot be attributed to judgment error. Furthermore, we show that the underweighting of small probabilities is also reflected in the best-fitting parameter values obtained when prospect theory, the dominant model of risky choice, is applied to the data.*

In the past several decades of decision-making research in experimental psychology, the predominant experimental paradigm has been to present summary symbolic descriptions of simple lotteries. For example, a gamble might be described as "an 80% chance of winning £4 and a 20% chance of winning £0." It is widely accepted that choice data obtained using descriptive problems imply that people overweight low probabilities and underweight high probabilities. In prospect theory (PT; Kahneman & Tversky, 1979), the dominant model of descriptive choice, objective probabilities and outcomes are transformed into their subjective counterparts and then combined multiplicatively. The transform of the outcomes into their subjective values is an S-shaped function, and the transform of probabilities into subjective decision weights is an inverse S-shaped function that overweights small probabilities and underweights probabilities near 1. The shape of this weighting function has also been tested directly (e.g., Bleichrodt, 2001; Gonzalez & Wu, 1999; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996).

Recently, researchers have revisited choice tasks in which objective information regarding the outcomes and probabilities is not initially known, but instead must be inferred from a sample of possible outcomes (e.g., Barkan, Zohar, & Erev, 1998; Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004; Weber, Shafir, & Blais, 2004). Most of these studies (e.g., Barron & Erev, 2003; Hertwig et al., 2004; Weber et al., 2004) have reported choice behavior that differs sharply from that observed in the descriptive paradigm. Crucially, choices appear to indicate an *underweighting* of small probabilities.

Hertwig et al. (2004) argued that reliance on small samples and overemphasis of outcomes from recent samples may explain the apparent underweighting of rare events in decisions from experience. Their "decisions from experience" paradigm is based on an initial sampling phase in which participants freely explore a pair of lotteries without cost by drawing samples without replacement from the underlying outcome distributions (e.g., a participant might sample the sequence $\{4, 4, 0, 4, 0, 4\}$

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Psychological Science RESEARCH, THEORY, & APPLICATION IN PSYCHOLOGY AND RELATED SCIENCES

from a distribution with a .8 chance of winning 4 points and .2 chance of winning 0 points). After this sampling phase, participants decide which lottery to play once for real.

Crucially, in such a sampling task, when there is a low-probability event and the sample is small, the number of times the event occurs in a given sample is generally positively skewed. In the case of the example just mentioned (.8 chance of winning 4 points and .2 chance of winning 0 points), suppose that 100 people draw only 10 samples each from this distribution. On average, 38 people will experience the rare outcome of 0 points fewer than two times, and will therefore underestimate the probability of receiving 0 points. This group will include 11 people who will not experience this outcome even once. Thirty people will experience 0 points exactly twice and will estimate the probability correctly, and 32 people will experience the zero outcome more than twice and will overestimate the probability. Although the asymmetry between underestimation and overestimation is small, Hertwig et al. (2004) argued that it is one of the sources of the underweighting of low-probability events. Fox and Hadar (2006) went further, arguing that what seems to be evidence for underweighting of low-probability events in decisions from experience is not really evidence for underweighting, but rather is entirely consistent with overweighting of low probabilities (as also occurs in decisions from description). According to this argument, when people experience a probability that is smaller than the objective probability because of the skew in small samples, they overweight the smaller experienced probability (as in PT), which results in a net effect of slight underweighting. In this view, apparent underweighting is not a psychological phenomenon at all, but results from the statistical properties of small samples.

Fox and Hadar (2006) also raised the possibility of distortion through judgment error, which might arise in the mapping from experienced frequencies to probabilities. Such distortion could occur at the first stage of the two-stage model of decision under uncertainty (Fox & Tversky, 1998; Tversky & Fox, 1995), during which probabilities of uncertain events are assessed subjectively before being further transformed by the weighting function. To evaluate this possibility, Fox and Hadar added an explicit probability-judgment task to the design, finding that probability judgments were well calibrated, and thus cannot underlie the apparent underweighting of rare events. Moreover, taking PT value- and weighting-function parameters that were reported by Tversky and Kahneman (1992) and originally fitted to descriptive problems, Fox and Hadar successfully applied these parameters to individual probability judgments and found a good fit with the observed choices.

The two experiments reported here tested the impact of sampling error directly, by eliminating it. In addition, the second experiment further examined the potential impact of judgment error.

EXPERIMENT 1: THE MATCHED-SAMPLING DESIGN

If the apparent underweighting of small probabilities is explained by the undersampling of rare outcomes—a possibility raised, in different ways, by both Hertwig et al. (2004) and Fox and Hadar (2006)—then it should be eliminated and reversed (to match overweighting in decision from description) if participants experience perfectly representative samples. This prediction was tested in Experiment 1.

Method

Seventy-five students at the University of Warwick received £2 for the completion of six choice tasks in the laboratory. The six decision problems were taken from Hertwig et al. (2004) and are summarized in Table 1.

TABLE 1

Results From Experiment 1: Percentage of Choices in the Direction of Overweighting of Small Probabilities and Differences Between the Description and Sampling Conditions

Choice problem	Option A	Option B	Description condition (n = 25)	Free-sampling condition (n = 25)	Matched-sampling condition (n = 25)	Difference between the description and free-sampling conditions	Difference between the description and matched-sampling conditions
1	**4, .8; 0, .2**	3, 1.0	64	36	52	+28 (z = 1.98, p = .024)	+12 (z = 0.86, p = .195)
2	**4, .2; 0, .8**	3, .25; 0, .75	72	56	60	+16 (z = 1.18, p = .119)	+12 (z = 0.9, p = .185)
3	−3, 1.0	**−32, .1; 0, .9**	64	16	28	+48 (z = 3.46, p < .001)	+36 (z = 2.55, p = .005)
4	−3, 1.0	**−4, .8; 0, .2**	64	32	68	+32 (z = 2.26, p = .012)	−4 (z = 0.3, p = .383)
5	**32, .1; 0, .9**	3, 1.0	48	8	16	+40 (z = 3.15, p < .001)	+32 (z = 2.43, p = .008)
6	**32, .025; 0, .975**	3, .25; 0, .75	52	28	28	+24 (z = 1.73, p = .042)	+24 (z = 1.73, p = .042)

Note. In the columns providing the descriptions of the options, each outcome (number of points won or lost) is followed by its probability of occurrence. The options including the rare event are highlighted in boldface. We calculated z statistics to test whether the difference between the conditions was significantly different from zero.

Participants were randomly assigned to one of three experimental conditions: a free-sampling condition, a matched-sampling condition, and a description condition. The first two conditions began with a sampling phase in which participants explored the two options represented by two buttons, "A" and "B," on a computer screen. The sampling phase was followed by a final decision phase in which they chose the option they would like to play once. The free-sampling condition followed the paradigm Hertwig et al. (2004) used: Participants could stop their exploration in the sampling phase as soon as they felt confident enough to make a decision, and outcomes were determined randomly for each participant. In the crucial matched-sampling condition, however, participants had to sample 40 outcomes from each option, in any order, before proceeding to the decision phase, and the frequencies of outcomes precisely matched the underlying probabilities, with the order of outcomes determined randomly for each participant. Thus, the decision problem with .8 probability of winning 4 points and .2 probability of winning nothing would be realized as exactly 32 trials with the 4-point outcome and 8 trials with the 0-point outcome, in random order. In the description condition, participants instead read summaries of the same lotteries, in the following format:

80% chance to win 4 points;
20% chance to win 0 points.

Participants were instructed to attempt to obtain as many points as possible across the six choice problems. At the end of the experiment, the lotteries were played randomly for each participant, and participants were informed of the total points they had won.

Results and Discussion

In the free-sampling condition, the median number of samples per choice problem (the two buttons combined) was 19. Thus, participants in this condition were restrained in their information search, as is typical for decision-from-experience formats. Across all lotteries, the rare event was encountered less frequently than expected in 50% of the sampling sequences. Thus, there was less undersampling of the rare event than reported by Hertwig et al. (2004). Nonetheless, in one third of all cases, the rare event was not encountered at all, so that participants were completely ignorant regarding the existence of the rare event—the extreme case of undersampling.

Table 1 shows the percentages of choices that were in the direction of overweighting of small probabilities, separately for each condition and choice problem, together with the z values for tests on the differences between conditions. These choice percentages were lower in the sampling conditions than in the description condition. Moreover, in many cases, the percentage was above 50% in the description condition but below 50% in the sampling condition, which implies an actual difference in modal choice. This was true for Problems 1, 3, 4, and 6 in the case of the free-sampling condition and for Problems 3 and 6 in the case of the matched-sampling condition. Following Hertwig et al. (2004), the differences in the percentages and the change in modal choice can be interpreted as actual reversals of choice in the direction of underweighting of small probabilities in the sampling conditions.

Averaging over the six choice problems, there was a significant effect of condition on the mean percentage of choices in the direction of overweighting, $F(2, 72) = 18.6$, $p < .0001$, $p_{rep} > .999$, $\omega = .65$. Planned contrasts revealed that sampling from the options instead of receiving a description led to a significantly smaller percentage of choices in the direction of overweighting of small probabilities, $t(72) = -5.59$, $p < .0001$, $p_{rep} > .999$ (two-tailed), $r = .55$, and that the decrease was stronger in the free-sampling condition than in the matched-sampling condition, $t(72) = -2.45$, $p = .017$, $p_{rep} = .933$ (two-tailed), $r = .28$. In other words, the effect was reduced but not eliminated in the matched-sampling condition, in which sample size was controlled and sample frequencies precisely matched the underlying probabilities. Thus, sampling error seems to explain only part of the difference between decisions from experience and decisions from description.

One possible explanation for why the effect was maintained even with matched, equal samples is that people's "mental samples" are smaller than the actual samples they have experienced. If so, the most recently sampled outcomes should be overrepresented and determine the final choices more strongly than less recently sampled outcomes, because they are more available in memory (e.g., Atkinson & Shiffrin, 1968). But such recency effects were not observed. Following Hertwig et al. (2004), we computed the expected values of the first and second halves of the experienced samples separately and found that the second half was no more reliable than the first half in predicting people's choices; this was true both in the free-sampling condition (69% vs. 65%), $t(24) = 0.54$, $p = .596$, $p_{rep} = .43$ (two-tailed), and in the matched-sampling condition (48% vs. 42%), $t(24) = 1.12$, $p = .272$, $p_{rep} = .67$ (two-tailed).

To investigate the extent to which established models can account for our results, we calculated the rate of correct predictions derived from PT. Fox and Hadar (2006) found that 63% of choices conformed to PT when they applied the median value- and weighting-function parameters from Tversky and Kahneman (1992) to their data using participants' probability judgments instead of the objective probabilities. Instead of applying a specific set of parameter values implying overweighting of small probabilities, we tested the performance of PT across a wider range of parameter values between 0 and 2, in steps of .01. This approach allowed us to evaluate the performance of the model under a variety of weighting functions that imply different degrees of underweighting, as well as overweighting, of small probabilities. The choices from different subjects were pooled, and parameters were estimated across all choices, separately for decision problems involving only gains (parameters α and γ) and decision problems involving only losses (parameters β and δ).

The contour plots in Figure 1 show the proportion of correct predictions as a function of the value- and weighting-function parameters. In the free-sampling condition, the highest proportion of correct predictions obtained under PT was .81. The regions with the highest fit, represented by the darkest shading in the figure, lie predominantly within the top halves of the plots, which are marked by weighting-function parameters greater than 1. Functions based on such parameter values imply underweighting of small probabilities. Conversely, the areas with the lowest fit (i.e., the brightest areas) are mostly in the lower halves of the plots. In the matched-sampling condition, the maximum proportion of correct predictions for PT was much lower, at .64. The contour plots for this condition show that this degree of fit was obtained across a wide range of weighting-function parameters including values implying both over- and underweighting of small probabilities.

In summary, this experiment demonstrates the robustness of the underweighting of small probabilities in decisions from experience, even when there is no sampling error and no recency effect. Furthermore, underweighting appears also to be reflected in the best-fitting parameter values for the PT model. However, this experiment does not rule out the possibility that people systematically misjudge probabilities from the sample they experience.

EXPERIMENT 2: MATCHED SAMPLING WITH ASSESSMENT OF JUDGMENT ERROR

In our second experiment, we added a probability-judgment task to the matched-sampling design of the first study to test directly for any systematic judgment biases.

Method

This Web-based experiment was completed by a total of 197 participants, including both students and the general population. The design was similar to that of the matched-sampling

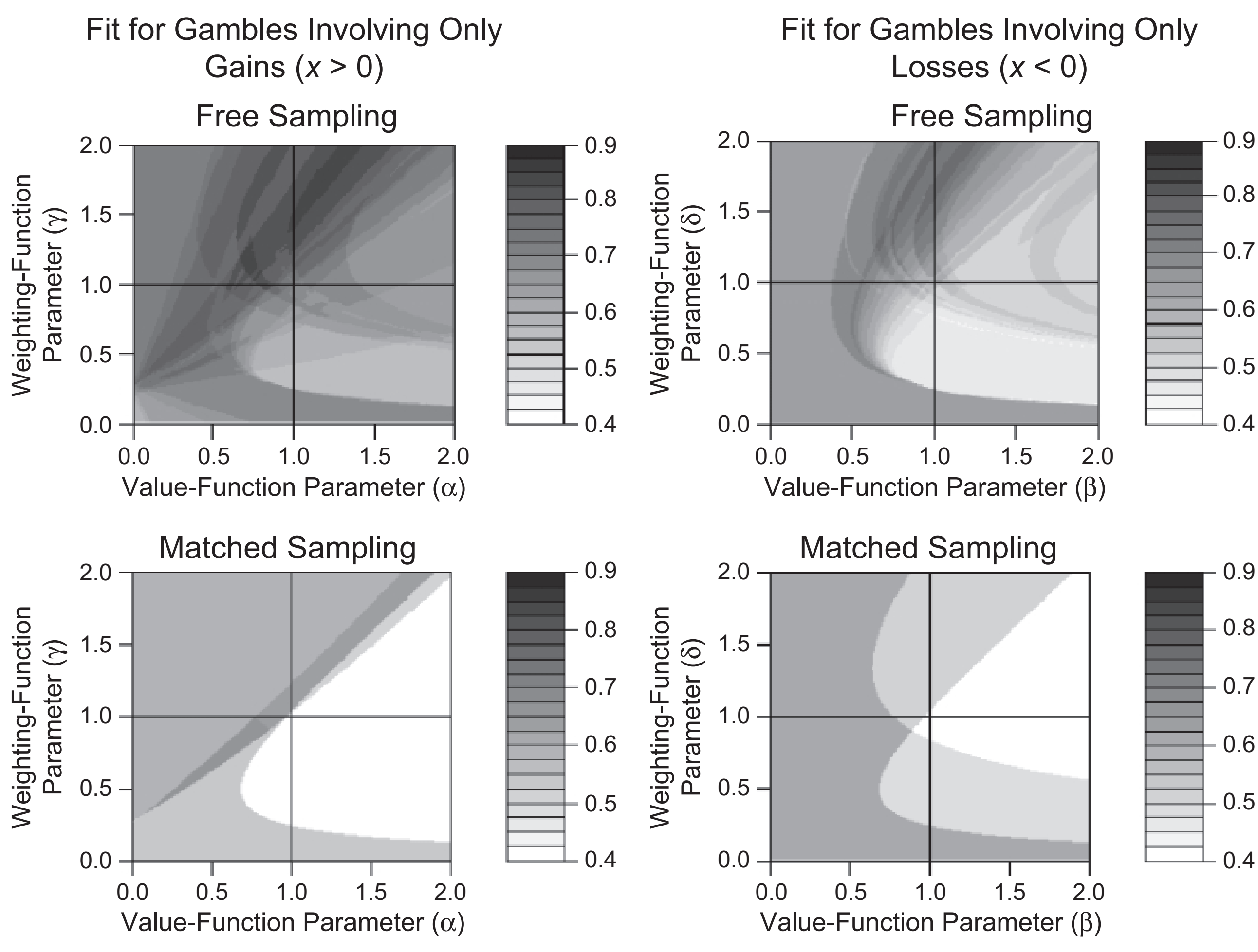

Fig. 1. Contour plots showing the proportion of correct predictions when prospect theory was applied to the data in the free-sampling (top row) and matched-sampling (bottom row) conditions of Experiment 1. The proportion of correct predictions was calculated for each combination of value- and weighting-function parameters between 0 and 2, in steps of .01. The regions with the darkest shading indicate the combinations providing the highest fit. Results are shown separately for the problems involving gains ($x > 0$), on the left, and the problems involving losses ($x < 0$), on the right.

TABLE 2

Percentage of Choices in the Direction of Overweighting of Small Probabilities: Comparison Between the Matched-Sampling Condition in Experiment 2 and the Description Condition in Experiment 1

Choice problem	Option A	Option B	Description condition (n = 25)	Matched-sampling condition	Difference between conditions
1	**4, .8; 0, .2**	3, 1.0	64	32 (10/31)	+32 (z = 2.39, p = .008)
2	**4, .2; 0, .8**	3, .25; 0, .75	72	39 (12/31)	+33 (z = 2.46, p = .007)
3	−3, 1.0	**−32, .1; 0, .9**	64	42 (13/31)	+22 (z = 1.64, p = .051)
4	−3, 1.0	**−4, .8; 0, .2**	64	45 (17/38)	+19 (z = 1.48, p = .07)
5	**32, .1; 0, .9**	3, 1.0	48	45 (14/31)	+3 (z = 0.22, p = .411)
6	**32, .025; 0, .975**	3, .25; 0, .75	52	26 (9/35)	+26 (z = 2.06, p = .02)

Note. In the columns providing the descriptions of the options, each outcome (number of points won or lost) is followed by its probability of occurrence. The options including the rare event are highlighted in boldface. In the matched-sampling condition, n varied across the choice problems, and the actual choice proportions are given in parentheses. We calculated z statistics to test whether the difference between the conditions was significantly different from zero.

condition in Experiment 1, with participants sampling from each button 40 outcomes that matched the underlying probabilities. In addition, an unexpected judgment task followed the decision phase. Participants estimated the number of times they had seen the rare event within the samples from the two buttons. Because participants might have expected a judgment task after subsequent problems and therefore might have started to use a counting strategy, we gave each participant only one of the six choice problems used previously.

Results and Discussion

Table 2 shows the percentage of choices in the direction of overweighting of small probabilities for each of the six choice problems. The percentages from the description condition in Experiment 1 are presented for comparison. For five of the six problems, the percentages were above 50% in the description condition and below 50% in the sampling condition, indicating reversals in modal choice in the direction of underweighting of small probabilities in the case of decisions from experience. Although sampling error was eliminated, the mean choice proportions (across all six problems) again differed significantly between the description and sampling conditions, $t(220) = 4.22$, $p < .0001$, $p_{rep} > .999$ (two-tailed).

The literature on frequency judgment has generally reported overestimation of low frequencies (e.g., Zacks & Hasher, 2002). However, if judgment error is responsible for the reversal in choice behavior, one would expect systematic underestimation of low frequencies experienced during sampling. We did not observe such underestimation. Participants' judgments were well calibrated; the correlation between judged and actual frequencies was high, $r(370) = .98$, $p < .0001$, $p_{rep} > .999$, and the mean absolute difference between these values was 1.57 (SD = 2.37).

Figure 2 shows the distribution of observed deviations between actual and estimated frequencies. An examination of the mean estimation errors showed small deviations in the direction of overestimation of low frequencies and underestimation of high frequencies; results of statistical tests of these values, in ascending order from low to high observed frequency, were as

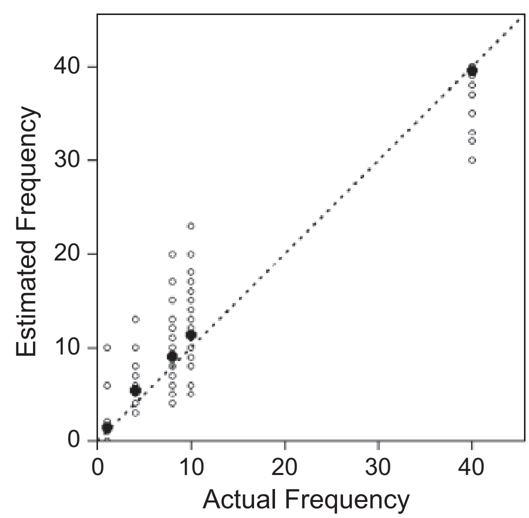

Fig. 2. Deviations of the frequency judgments for the rare events as a function of the actually experienced frequencies. The estimated frequencies (y-axis) are plotted against the actual frequencies (x-axis). For the problems with a single, sure option, participants could provide estimates for the common event only (frequency of 40). The dotted line indicates perfect calibration between estimated and actual frequency. The white dots show the spread of the observed estimates for the different frequencies. The estimation means for the different frequencies are indicated by the black dots.

follows: $t(34) = 1.46$, $p = .154$, $p_{rep} = .76$; $t(61) = 5.16$, $p < .001$, $p_{rep} > .999$; $t(90) = 3.18$, $p = .002$, $p_{rep} = .98$; $t(64) = 2.71$, $p = .009$, $p_{rep} = .95$; $t(118) = 2.89$, $p = .005$, $p_{rep} = .97$ (all tests two-tailed).

As in Experiment 1, we predicted choices using outcomes from the first and second halves of the sampling sequences. Again, recency weighting was not found, as the two halves did not differ in their accuracy of predicting participants' choices (51% and 48%, respectively), McNemar $\chi^2(1, N = 197) = 0.021$, $p = .885$, $p_{rep} = .2$.

Using the frequency judgments, it was also possible to calculate model fits for the two-stage model (Fox & Tversky, 1998; Tversky & Fox, 1995). As Figure 3 shows, for both the two-stage model (parameters estimated on the basis of judged probabilities) and the PT model (parameters estimated on the basis of experienced probabilities), the highest rate of correct predictions was obtained with weighting-function parameters greater than 1 (upper halves of the contour plots in the figure). Thus, the best-fitting parameter values for each model implied weighting functions with a shape that incorporated underweighting of small probabilities. The highest rate of correct predictions was similar for the two models: 62% for the PT model and 65% for the two-stage model.

GENERAL DISCUSSION

The matched-sampling design we used provides additional support for the robustness of the apparent underweighting of small probabilities in decisions from experience: Small probabilities were underweighted even when the influence of statistical sampling error, due to small sample sizes, was eliminated. Therefore, sampling error cannot be the sole explanation for the phenomenon. Both of our experiments also provide evidence for the occurrence of underweighting in the absence of recency weighting. Moreover, in light of the well-calibrated frequency estimations (with a slight tendency to overweight small fre-

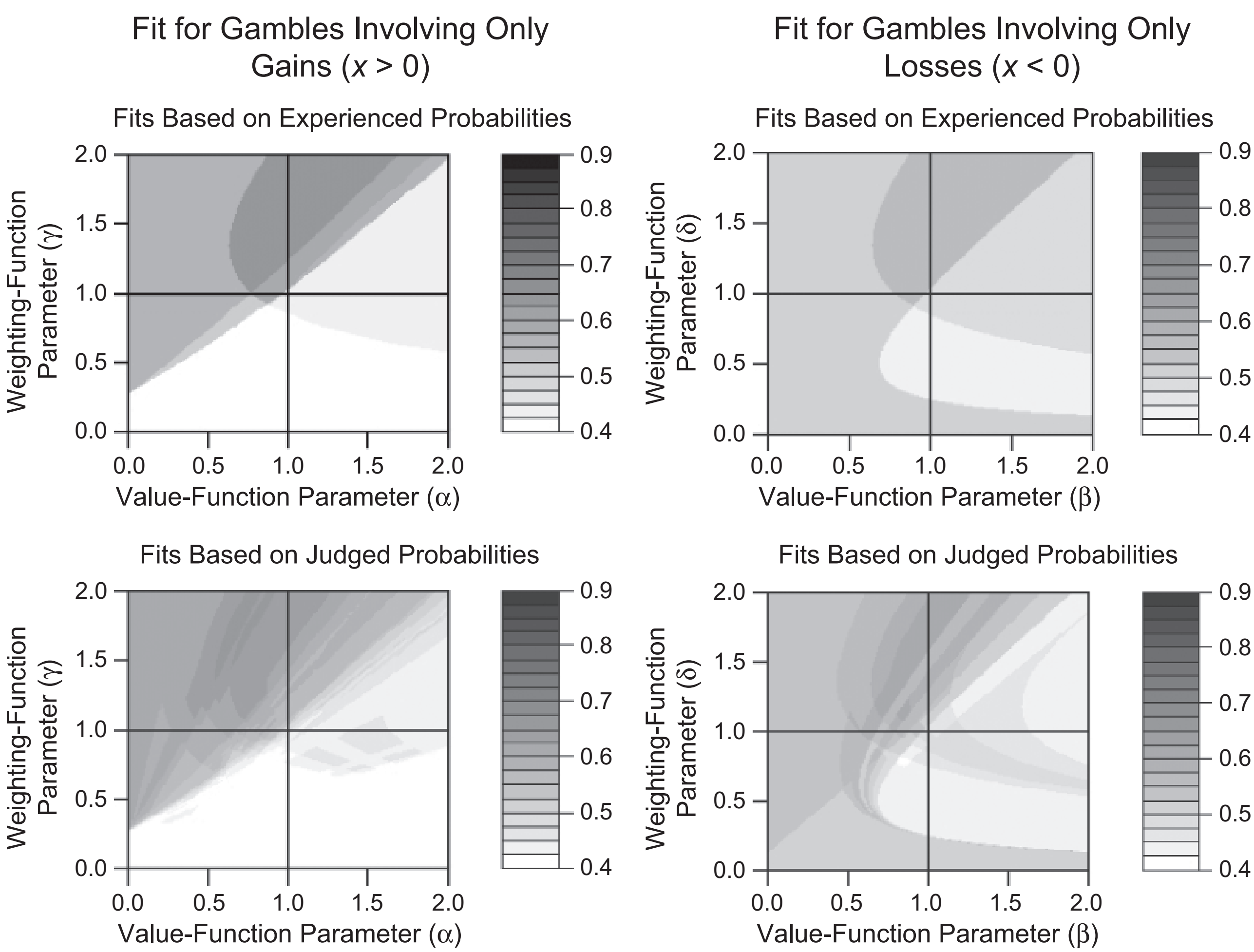

Fig. 3. Contour plots showing the proportion of correct predictions provided by prospect theory (top row) and the two-stage model (bottom row) for the matched-sampling condition in Experiment 2. The proportion of correct predictions was calculated for each combination of value- and weighting-function parameters between 0 and 2, in steps of .01. The regions with the darkest shading indicate the combinations providing the highest fit. Results are shown separately for the problems involving gains ($x > 0$), on the left, and the problems involving losses ($x < 0$), on the right.

quencies), judgment error in the form of underestimation of small probabilities from frequency data can also be excluded as an explanation. Finally, the best fits of PT to these data were obtained under probability-weighting functions with parameters that imply underweighting of small probabilities and shapes inverse to those established for decisions from description. The results for the two-stage model suggest that the same results are obtained regardless of sampling error.

With all the candidate explanations disqualified, it remains unclear what exactly causes the underweighting of small probabilities in decisions from experience. In order to gain a deeper understanding of the cognitive processes involved, it might be important to extend the range of the models considered. One alternative class of models that seems to be able to describe behavior in experiential choice tasks well stems from research on reinforcement learning (e.g., March, 1996). Other approaches could be derived from work on probability learning (e.g., Goodnow, 1955; Nicks, 1959; Restle, 1961), which shows that responses in binary choice tasks can be modeled on the basis of subunits of a sequence, such as runs or recurring patterns. There is also evidence suggesting that lotteries are evaluated relative to one another, and that preferences can depend on the set of options available (e.g., Stewart, Chater, Stott, & Reimers, 2003; Wedell, 1991). Such findings could apply to the evaluation of options in decisions from experience. An examination of the sampling process in the experiments reported here showed that the majority of participants switched frequently between options (mean number of switches = 10.77, SD = 13.84), instead of exploring options in two separate blocks (switching only once). Such behavior could facilitate the evaluation of the options relative to each other throughout the sampling process. Thus, depending on the extent of switching between options and the resulting partitioning into smaller subsamples, even under matched sampling the two options could be evaluated on the basis of comparisons between subsamples that have outcome sequences that no longer represent the objective probabilities of the options. This perspective suggests a different view or interpretation of the nature of the experiential choice tasks we used and extends the range of plausible strategies that have to be considered in order to explain the observed behavior.

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