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A Change-of-Process Theory for Contextual Effects and Preference Reversals in Risky Decision Making

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Three experiments were conducted to investigate contextual effects and response mode effects (e.g., preference reversals) in risky decision making. Judgments of the worth of binary gambles were examined using two different contexts (positively and negatively skewed distributions of expected values) and two different response modes (attractiveness ratings and buying prices). Changes in the response mode affected the preference order of gambles, and changes in the context due to variations in skewing influenced the metric properties of the judgments but had a minimal effect on preference orders. Data were inconsistent with contingent weighting theory (Tversky, Sattath, & Slovic, 1988) and expression theory (Goldstein & Einhorn, 1987). Results could be described by a change-of-process theory which assumes that the method of elicitation influences the manner in which people combine information and arrive at judgments. Under certain conditions, attractiveness ratings could be described by an additive combination of subjective probability and utility (s and u), whereas pricing judgments were accounted for by a multiplicative function, with the same scales of s and u in both tasks. When the range of outcomes included zero and negative values, preference orders for attractiveness ratings of gambles changed. This change in rank order was consistent with the hypothesis that inclusion of these levels caused more subjects to use a multiplicative rule for combining u and s when rating the attractiveness of gambles. Thus, preference reversals can be explained by the theory that the combination rule changes, while utilities and subjective probabilities remain constant.

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INTRODUCTION

The concept of preference is central to most economic theories of decision making. Preferences are operationalized in terms of observed choice (e.g., we "prefer" A to B if we select A over B when given both options) and price (e.g., we "prefer" A over B if we assign a higher selling price to A than to B). Procedural invariance (Tversky, Sattath, & Slovic, 1988) says that the same rank order of options will occur regardless of the method used to operationalize preference. However, recent evidence demonstrates that preference orders are influenced by the response mode (Slovic & Lichtenstein, 1983) and possibly by the context provided by other stimuli (Huber, Payne & Puto, 1982; Schoemaker, 1982). The purpose of the present paper is to examine the effects of context and response mode on judgments of the worth of risky options.

Response Mode Effects

A well-known example of response mode effects was reported by Lichtenstein and Slovic (1971) and Lindman (1971). Lichtenstein and Slovic (1971) presented subjects with pairs of gambles matched on expected value. For example, one of the gamble pairs they used was Gamble A, a .97 chance to win $4, otherwise lose $1, and Gamble B, a .31 chance to win $16, otherwise lose $1.50. Lichtenstein and Slovic obtained both choices and minimum selling prices. If selling prices reflect preferences and if the same psychological process (or rule for combining utilities and subjective probabilities) underlies both selling price and choice, then the two procedures should produce the same preference order over gambles. When asked which gamble they would prefer to play, subjects tended to choose Gamble A (with the larger probability of winning) over Gamble B (with the larger amount to win). Yet when asked to state the lowest price they would accept to sell the gambles, subjects reported a higher selling price for Gamble B than Gamble A.

Such reversals of preference have been replicated by several others (Hamm, 1979; Grether & Plott, 1979; Mowen & Gentry, 1980; Lichtenstein & Slovic, 1973; Reilly, 1982; Pommerehne, Schneider, & Zweifel, 1982). Goldstein and Einhorn (1987) found similar results for other pairs of response modes as well, including attractiveness ratings vs selling prices (i.e., Gamble A was rated more attractive than Gamble B, but Gamble B had a higher selling price than Gamble A). Other types of preference reversals have been demonstrated by Birnbaum and Sutton (1992) and Birnbaum, Coffey, Mellers, and Weiss (1992). A great deal of theoretical work has also been done on the preference reversal phenomenon (Holt, 1986; Loomes & Sugden, 1983; Karni & Safra, 1987; Bostic, Herrnstein, & Luce, 1990; Tversky, Slovic & Kahneman, 1990).

Psychological Theories

It is useful to consider judgment as a composition of functions (Birnbaum, Parducci, & Gifford, 1971), as shown in Fig. 1. For example, attractiveness ratings or buying prices can be decomposed into three processes represented by the functions, H, C, and J. Subjective values of the stimuli (s_i and u_j representing subjective probabilities and utilities) are functionally related to the corresponding physical values of probabilities and dollar amounts (P_i and A_j) by psychophysical functions, H. H_P and H_A might represent the psychophysical functions for probability and amount, respectively. Bernoulli (1735/1954) proposed a log function for H_A relating money to satisfaction. Subjective values are then combined by a second process, C, where $\Psi = C(s_i, u_j)$. For example, C might be subjective expected utility theory. Finally, the judgment function, J, translates subjective impressions, Ψ, to overt responses, R. For example, R might be a buying price or a judgment of attractiveness on a category rating scale.

The judgment function (J) is useful to explain how subjects convert an overall impression into a response along a scale imposed by the experimenter. Typically, the J function is assumed to be a monotonic function of the overall impression. Past research has shown that the J function depends on the overall distribution of stimuli and responses (Birnbaum, 1982; Mellers & Birnbaum, 1982). Birnbaum *et al.* (1971) noted however, that in some cases, the context affecting J might be determined by the particular combination of stimulus information presented on a single trial. They distinguished between judgmental effects that are influenced by the *within-set context* (stimulus information on a given trial) vs those affected by the *between-set context* (stimulus information across trials).

This paper will address three psychological theories of preference reversals. Two previously proposed theories (Tversky *et al.*, 1988; Goldstein & Einhorn, 1987), which attribute preference reversals to changes in H and J, are contrasted with a change-of-process theory, which attributes preference reversals to changes in C. These theories are now briefly reviewed and will be discussed in more detail later.

Expression theory. Expression theory (Goldstein & Einhorn, 1987) attributes preference reversals to differences in the output processes that

$$\begin{tikzcd}
 & H & C & J \\
P_i \arrow[r] & s_i \arrow[dr] & & \\
 & & \Psi_{ij} \arrow[r] & R_{ij} \\
A_j \arrow[r] & u_j \arrow[ur] & &
\end{tikzcd}$$

FIG. 1. Schema for analysis of judgment.

transform the subjective worth of a gamble into a response. This theory attributes rank order changes to different judgment processes influenced by the within-set context, as defined in Birnbaum *et al.* (1971). Each gamble is assumed to have a "proportional adjustment" that reflects the worth of the gamble relative to the utility of the best and worst outcome. Subjects are theorized to map this proportional adjustment to a comparable point having the same proportional adjustment for each response mode. This mapping occurs by means of a "subjective interpolation process" (a judgment process). The proportional adjustment of a gamble on the payoff scale is defined with respect to the gamble's best and worst monetary outcomes. The proportional adjustment of a gamble on a rating scale is defined with respect to the highest and lowest permissible attractiveness ratings.

Expression theory implies that after response to gambles from two or more tasks are transformed to their proportional adjustments (a transformation that differs for each gamble), proportional adjustments for the same gambles across tasks should be monotonically related. Thus, expression theory assumes that the rank order changes across tasks are attributable to different judgment functions (J in Fig. 1) that vary depending on the outcome (i.e., the functions J_j vary for different outcomes).

Contingent weighting theory. A second approach that predicts differential preference orders across response modes is contingent weighting theory (Tversky *et al.*, 1988). Tversky *et al.* propose a hierarchy of contingent trade-off models to account for discrepancies between judgment and choice. A special case of the trade-off models is the contingent weighting model [Eq. (5), Tversky *et al.*, 1988]. According to this model, the trade-off between attributes depends on the nature of the response, and the weight associated with each attribute varies as a function of its compatibility with the output. In one application, Tversky *et al.* (1988) use the contingent weighting model to account for discrepancies between ratings and prices. They propose that the value of a gamble with some probability, p, of winning an amount, A, otherwise winning nothing, is a multiplicative function of probability and payoff. Both probability and payoff are assumed to have weights that depend on the response scale. Using additive, linear, multiple regression with logs of p and A as predictors, Tversky *et al.* (1988) argue that the relative weight associated with log payoff is greater in the pricing task than in the rating task. This greater weight is attributed to the compatibility of payoffs and monetary responses in the pricing task.

Contingent weighting theory assumes that shifts in rank orders are attributable to changes in the weights of the attributes. Since the stimulus parameters (either weights or scale values) depend on the method of elicitation, this account can be thought of as attributing preference reversals to specific changes in the psychophysical functions (H in Fig. 1). Tversky *et al.* (1988) do present a more general contingent tradeoff model in which scales or processes can change, depending on the task. However, this more general model makes no predictions about the conditions under which scales or processes will vary.

Change-of-process theory. A third possibility, change-of-process theory, assumes that the stimulus parameters (subjective probabilities and utilities) remain constant over response modes, but the process by which subjects combine information varies as a function of the task. The possibility of changing decision strategies was discussed by Payne (1982), who theorized that decision processes might depend on the response mode, the effort required, the accuracy needed, etc. This idea was also considered by Lichtenstein and Slovic (1971), Schkade and Johnson (1989), and Johnson, Payne, and Bettman (1988), among others. The present theory extends these ideas by postulating specific models for ratings and prices of binary gambles. In particular, probabilities and payoffs are assumed to be combined multiplicatively in the pricing task, but additively in the rating task. Furthermore, the change-of-process theory has the added premise of scale convergence (Birnbaum, 1974; Birnbaum & Veit, 1974). According to the change-of-process theory, combination rules (C in Fig. 1) vary with the task, and the psychophysical functions (H in Fig. 1) remain constant.

There are some interesting connections between the contingent trade-off models and the change-of-process theory. When the stimuli involve binary gambles with some probability of receiving an amount (otherwise zero), and the amounts are either all positive or all negative, the change-of-process theory is a special case of a contingent trade-off model [Eq. (4), Tversky *et al.*, 1988]. The contingent trade-off model asserts that probabilities and amounts are decomposable to an additive structure in both tasks. This form of contingent trade-offs could imply changing processes, since both the additive and the multiplicative models that constitute the change-of-process theory can be transformed to additivity.

Contingent trade-off models have not been developed for cases when the stimuli involve binary gambles with some probability of winning an amount, otherwise losing another amount. The change-of-process theory predicts that ratings should be consistent with a sign-dependent additive structure, but prices should not.

Contextual Effects

In judgment research, it is well known that the response to a stimulus depends not only on its subjective value but also on the other stimuli presented for judgment. For example, a 50 g weight may be called either "heavy" or "light" depending on the other weights presented for judgment (Helson, 1964; Parducci & Perrett, 1971; Birnbaum, 1974). Contextual effects have been shown to occur not only in psychophysical judgments but also in complex social judgments such as morality, happiness, fair salaries, and fair taxes (Parducci, 1968, 1982; Mellers, 1982, 1986). Results are consistent with the view that certain types of contextual manipulations (i.e., changes in the stimulus distribution) can affect the H and/or the J functions in systematic ways (Mellers & Birnbaum, 1982). These types of contextual effects have received less attention in the decision-making literature than other domains of judgment research.

The present paper investigates contextual effects in attractiveness ratings and buying prices. It seems plausible that attractiveness ratings might depend on the context, since the concepts of "attractiveness" and "unattractiveness" for gambles seem to require comparison with the available options. Buying prices, however, might be less influenced by contextual effects, since people presumably have considerable familiarity with monetary prices; hence, the context experienced outside the laboratory may override any attempt to manipulate the context inside the laboratory. For example, if a subject knows from experience that a house would cost $250,000 in a particular neighborhood, he or she might be resistant to laboratory manipulations of context when judging its value.

Mellers and Birnbaum (1982, 1983) investigated contextual effects due to changes in the stimulus distribution in multiple-stimulus judgments. They showed how one can determine the locus of the effects by examining the rank order of certain common stimuli nested inside different contexts. If the rank orders of the common stimuli differ between two or more contexts, then contextual effects are presumed to occur *before* stimulus combination or comparison, i.e., in the psychophysical functions. Changes in the scale values can produce different rank orders. However, if the rank orders of the common stimuli in different contexts are the same, contextual effects can be represented in the J function, *after* stimulus combination or comparison. It will be argued later (Experiment 3) that certain types of contextual manipulations can influence the way in which information is combined (C in Fig. 1).

Contextual effects due to variations in the stimulus distribution in attractiveness ratings or buying prices might occur in the psychophysical function (H in Fig. 1) or in the judgment function (J in Fig. 1). If the context influences H, then utilities and subjective probabilities depend on the stimulus distribution. If the context affects only the judgment function, then subjects would assign differential responses to the same stimulus combination without changing the rank order of the judgments.

EXPERIMENT 1: CONTEXT AND RESPONSE MODE EFFECTS IN GAMBLES WITH A POSITIVE AND A ZERO OUTCOME

Method

Subjects served in one of four conditions, constructed from a 2 × 2 (response mode by context) factorial design. They either rated the attractiveness of gambles or stated the maximum amount they would be willing to pay to play the gambles. Judgments were made in one of two contexts in which the distribution of expected values (across gambles) was either positively or negatively skewed.

Stimuli and design. Gambles were displayed in the format shown in Fig. 2. The circles were 1 in. in diameter and were said to represent spinner devices. The outcome depended on whether the spinner pointed to the black or the gray region. All of the gambles had two outcomes; one was a positive amount and the other was zero. In each condition, there were 36 common gambles constructed from a 6 × 6 (probability of winning by amount to win) factorial design. The proportion of the black region (as in Fig. 2) matched the probability of winning a specified amount. Probability values were .05, .09, .17, .29, .52, and .94; amount levels were \$3.00, \$5.40, \$9.70, \$17.50, \$31.50, and \$56.70. These levels were chosen to be geometrically spaced (within rounding) to produce gambles varying in amount and probability having nearly equal expected values, which are presented in Table 1.

These 36 common gambles were embedded in two different contextual conditions. In each condition, 195 additional contextual gambles were included for judgment. Figure 3 shows the common stimuli (solid squares) and contextual stimuli in the positively skewed condition. Contextual stimuli are shown with numbers (1, 2, 3, 5, or 7) referring to the frequency with which each gamble was presented. The marginal distributions of probability and amount, as well as the joint distribution of expected values, were positively skewed. The negatively skewed condition used the same common stimuli, and the contextual stimuli were reflected about the

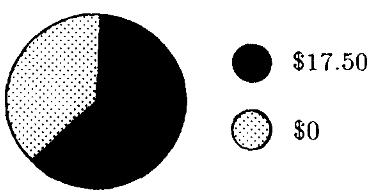

FIG. 2. An example stimulus. The black region corresponds to a .63 probability of winning \$17.50. The gray region represents a .37 probability of winning zero.

TABLE 1
EXPECTED VALUES FOR GAMBLES IN EXPERIMENT 1

	Amount					
Probability	$3.00	$5.40	$9.70	$17.50	$31.50	$56.70
0.05	.15	.27	.49	.88	1.58	2.84
0.09	.27	.49	.87	1.58	2.84	5.10
0.17	.48	.86	1.55	2.80	5.04	9.07
0.29	.87	1.57	2.81	5.08	9.14	16.44
0.52	1.56	2.81	5.04	9.10	16.38	29.48
0.94	2.82	5.08	9.12	16.45	29.61	53.30

major diagonal of the stimulus design in Fig. 3, making all three distributions (both marginals plus the joint) negatively skewed.

Instructions. In the rating task, subjects were asked to rate the attractiveness of each gamble using a scale from 0 to 80 as follows: 0 = Neutral, 20 = Slightly Attractive, 40 = Attractive, 60 = Very Attractive, and 80 = Very, Very Attractive. Subjects were shown the most attractive gamble (.94 chance to win $56.70) and the least attractive gamble (.05 chance to win $3.00), and they were instructed to rate the other gambles relative to those extremes. In the buying price task, subjects were asked to judge the maximum amount they would be willing to pay to play each gamble.

Procedure. Subjects were presented with 30 representative warm-up trials (pie charts and associated outcomes, as in Fig. 2) to familiarize them

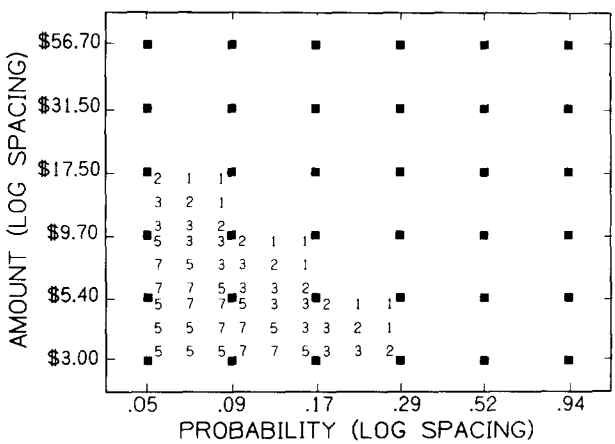

FIG. 3. Gambles used in the positively skewed distribution of expected values in Experiment 1. Amount to win is plotted on the ordinate and probability on the abscissa. Common stimuli are represented as solid squares. Numbers show "contextual stimuli" which were presented with frequencies corresponding to the numbers.

with the task, the range of the stimuli, and the skewing of the context. After the warm-up trials, subjects were given 231 test trials (36 common and 195 contextual stimuli), presented randomly in booklets. There were 10 gambles in a random order on each page, and page orders were counterbalanced using two latin square designs. Subjects worked at their own paces and completed the task in approximately 1 h.

Participants. Subjects in all three experiments presented in this paper were undergraduates at the University of California at Berkeley, who received credit in a lower division psychology course for their participation. There were approximately 40 different subjects in each of the four conditions. A few additional subjects were tested who did not follow instructions and were excluded from the analyses.

Results and Discussion

Response mode effects. Figure 4 presents mean attractiveness ratings

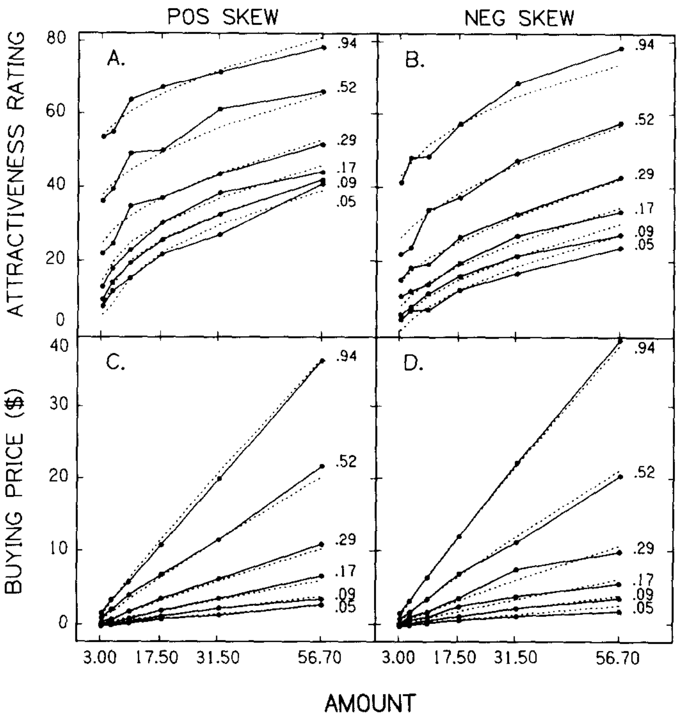

FIG. 4. Mean attractiveness ratings (upper panels) plotted against amount to win with a separate curve for each level of probability and a separate panel for each context. Solid lines connect data, and dashed lines show predictions of the change-of-process theory. Lower panels display mean buying prices for the same gambles, plotted as in the upper panels. Note that the shape of the curves and rank orders are different in the upper and lower panels.

(upper panels) and mean buying prices (lower panels) for the common gambles from the positively and negatively skewed contexts in the left and right panels, respectively. Data are shown as a function of the amount to win with a separate curve for each level of the probability of winning. Dashed lines are the predictions of the change-of-process theory which will be discussed later. The curves in the upper panels of Fig. 4 appear nearly parallel. Parallelism could result from averaging of individual strategies in which subjects attend to only one dimension, either probability or amount. Individual subject graphs were examined, and the overwhelming majority of subjects showed effects of both factors.

The lower panels in Fig. 4 show mean buying prices for the two contexts, plotted as in the upper panels. The pattern of results is different from that found in the upper panels for ratings; the curves form divergent fans of probability by amount. Furthermore, attractiveness ratings differ across gambles of equal expected value; gambles with larger probabilities of winning tend to receive higher attractiveness ratings than gambles with larger amounts to win, consistent with previous findings (Goldstein & Einhorn, 1987). Unlike results from the rating tasks, gambles with the same expected values are assigned similar buying prices, although there is a slight tendency to assign higher prices to the gambles with larger amounts to win than the gambles with larger probabilities of winning.

There are a number of other studies that should be mentioned in light of the present results. Parallelism in attractiveness ratings of gambles has been found by Levin, Johnson, Russo, and Delden (1985) as a function of the probability of winning and amount to win. Stevenson (1986) also obtained roughly parallel curves for ratings of investments described in terms of the probability of a success, the magnitude of the potential gain, and the time delay before the payoff. However, she interpreted her results in terms of a multiplicative combination process with a nonlinear judgment function. Finally, Shanteau (1974) asked subjects to rate the worth of bets consisting of some probability of winning a prize (e.g., a watch, a bicycle, a television, etc.). Although worth ratings seem similar to attractiveness ratings, Shanteau obtained bilinear fans that resembled the lower panels of Fig. 4. This result might be accounted for by the anchors on his response scale which said "Worthless" at the lower end and "Sure Thing to Win $75" at the upper end in one condition and "Sure Thing to Win a Television" in another condition. Subjects may have rated bets by anchoring the top of the scale with $75 or a cash equivalent for the television set, and the remaining gambles may have been judged using cash equivalents.

Rank order changes across response modes are consistent with the preference reversal phenomenon.[1] For example, in both contexts, the .94 chance of winning $3.00 is given a higher attractiveness rating than the .05 chance of winning $56.70. Mean ratings in the positively skewed context are 55 vs 42 on a scale from 0 to 80. However, the .05 chance of winning $56.70 has a higher buying price than the .94 chance of winning $3.00. Mean prices in the positively skewed context are $3.12 vs $2.03.

Percentages of preference reversals were computed by comparing pairs of gambles with the same expected values and counting the number of instances for which the rank order of preferences reversed across tasks. One type of preference reversal, referred to hereafter as "expected," occurs when the gamble with the higher probability of winning has a higher rating *and* the gamble with the larger payoff has a higher buying price. The other type of reversal, referred to as "unexpected," occurs when the gamble with the higher probability of winning has a higher buying price *and* the gamble with the larger payoff has a higher rating. Of the 55 comparisons, there were 41 and 55% "expected" preference reversals for the means in the positively and negatively skewed contexts, respectively. In contrast, there were only 2 and 9% "unexpected" preference reversals in the positively and negatively skewed contexts, respectively. In both contexts, there were significantly more "expected"' reversals than "unexpected" reversals; $\chi^2_{(1)}$ statistics were 20 and 18 for the positively and negatively skewed contexts, respectively.

Another way to assess changes in rank order is to compare nondominated pairs of gambles with unequal expected values. Nondominated pairs contain one gamble with a higher probability of winning and another gamble with a higher amount to win. Differences in expected values for these gambles ranged from $0.21 to $26.66. Of the 170 gamble pairs, there were 13 and 14% "expected" preference reversals in the means for the positively and negatively skewed contexts, respectively, as opposed to 2 and 1% in the opposite direction. Once again, there were significantly more "expected" than "unexpected" reversals; $\chi^2_{(1)}$ statistics were 14 and 19 for the positively and negatively skewed contexts, respectively. Thus, preference reversals occurred systematically for gamble pairs with equal and unequal expected values.

Changes in preference orders can be found at the individual subject level as well as the aggregate level. For example, 54% of the subjects in the attractiveness rating tasks rated the .94 chance of winning $3.00 as more attractive than the .17 chance of winning $56.70 (vs 35% who had the opposite order). In comparison, 89% of the subjects in the buying

[1] Although these preference reversals are based on between-subject designs, they are consistent with those found using within-subject designs.

price tasks assigned a higher price to the gamble with a .17 chance of winning \$56.70 than to the gamble with a .94 chance of winning \$3.00 (vs 10% who did the opposite).

Contextual effects. Effects of the stimulus distribution on attractiveness ratings are seen by comparing the upper left and right panels of Fig. 4. Each of the common gambles in the positively skewed condition is rated more attractive than the corresponding gamble in the negatively skewed condition. In addition, effects of the context interact with probability and amount. In the positively skewed context, vertical differences between the curves decrease from left to right (i.e., the curves converge). However in the negatively skewed context, vertical differences between the curves increase from left to right (i.e., the curves diverge). Data for the majority of subjects (60% in each context) match the patterns of convergence and divergence in the means. In contrast, the effect of context in buying prices is minimal, as seen by comparing the lower left and right panels of Fig. 4.

Figure 5 presents contextual effects by plotting ratings and prices of the common gambles from the two stimulus distributions, with a separate curve for each level of probability. If there were no effect of the context, points would fall on the identity line. However, for the rating task, all of the 36 points are above the identity line; ratings in the positively skewed context are consistently higher than ratings in the negatively skewed context. On average, common gambles in the positively skewed context are rated 10 points higher than the same gambles in the negatively skewed context. For the pricing task, points tend to fall close to the identity line;

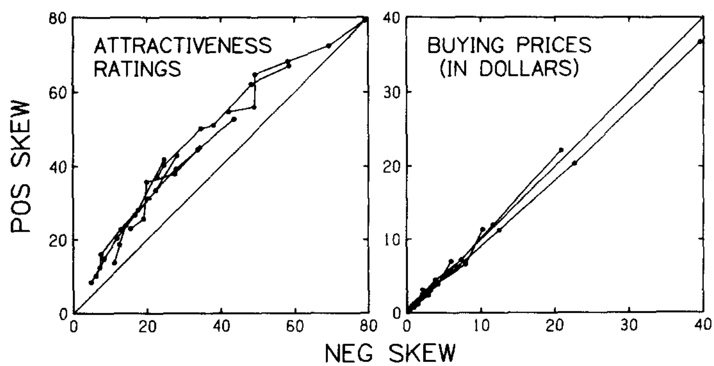

FIG. 5. Contextual effects due to manipulation of the stimulus distribution for the two tasks. Mean judgments from the positively skewed context are plotted against those from the negatively skewed context, with a separate curve for each level of probability. Left and right panels show results for attractiveness ratings and buying prices, respectively.

prices for common gambles are approximately the same in the two contexts. Points in both panels appear to fall close to a single curve, which implies that the rank orders are similar in the two contexts. The relationship between ratings in the positively and negatively skewed contexts is consistent with a range-frequency interpretation (Parducci, 1968, 1974) of the judgment function. Range-frequency theory predicts that the curve should fall above the identity line and be concave downward for these distributions.[2]

Tests among the three theories. According to expression theory (Goldstein & Einhorn, 1987), $u(G)$ is the subjective worth of a gamble with some probability, p, to win an amount, W, and probability $1 - p$ to lose an amount, L, as follows:

$$u(G) = u(W) - \Delta(u(W) - u(L)), \tag{1}$$

where Δ is a weight between 0 and 1. Solving for Δ gives

$$\Delta = \frac{u(W) - u(G)}{u(W) - u(L)}. \tag{2}$$

Here, Δ can be thought of as the proportional adjustment in the utility of the gamble due to the uncertainty of the outcomes and other situational factors.

Expression theory postulates that when subjects state their selling prices, they establish a correspondence between utility and monetary scales. A point is sought on the monetary scale for which the proportional adjustment in money matches the proportional adjustment in utility. Presumably, the same process holds for buying prices. The proportional adjustment on the monetary scale is

$$\Delta' = \frac{W - B}{W - L}, \tag{3}$$

where B is the buying price for the gamble.

[2] Range-frequency theory asserts that the response to a stimulus is a compromise between its rank in the stimulus distribution and its position relative to the endpoints. Therefore, when the stimulus distributions are positively and negatively skewed over the same intervals, the data for positively skewed distributions should be concave downward relative to the negatively skewed distributions.

With attractiveness ratings, the subject matches the proportional adjustment of the gamble to the proportional adjustment on the attractiveness rating scale. If the scale is 0 to 80, the proportional adjustment becomes

$$\Delta'' = \frac{80 - R}{80 - 0}, \tag{4}$$

where R is the attractiveness rating of the gamble.

Expression theory predicts that when subjects make ratings and prices of the same gambles, the proportional adjustments (Δ' and Δ'') should be monotonically related. To test this prediction, attractiveness ratings and buying prices were converted to proportional adjustments according to Eqs. (3) and (4). Figure 6 presents proportional adjustments for buying prices plotted against those for attractiveness ratings, with a separate curve for each level of probability. Data from the positively and negatively skewed contexts are shown in the right and left panels, respectively. In both panels, the points do not fall along a single curve as expected if Δ' and Δ'' were monotonically related. Instead, the two sets of proportional adjustments are nonmonotonically related. Proportional adjustments from the pricing tasks are primarily a function of probability; whereas proportional adjustments from the rating tasks vary with both probability and amount. In sum, changes in rank orders due to different response modes do not appear to be consistent with expression theory.

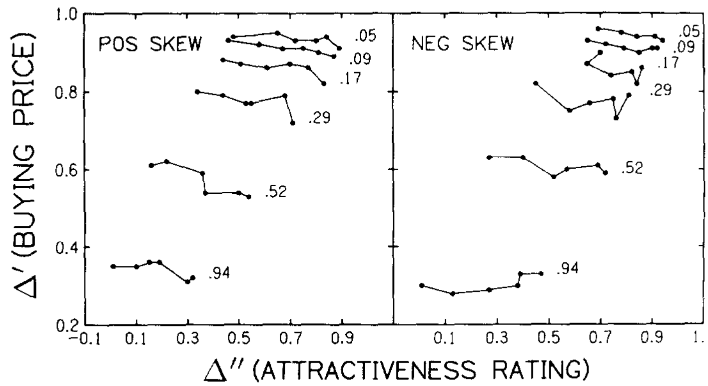

FIG. 6. Proportional adjustments from the pricing task plotted against those from the rating task in the two contexts, with a separate point for each of the common gambles. Each curve connects gambles with the same probability of winning. Expression theory implies that these proportional adjustments should be monotonically related, i.e., they should fall along a single curve. Results are inconsistent with the theory.

According to contingent weighting theory [Eq. (5), Tversky *et al.*, 1988], attractiveness ratings of simple gambles $(A, p; 0)$ are represented

$$R = J(p^a \cdot A^b), \tag{5}$$

where R is the attractiveness rating for a gamble with probability, p, of winning an amount, A, a and b are the weights of probability and amount, represented as exponents, and J is a strictly monotonic judgment function. Selling prices, and presumably buying prices, are represented

$$P = J^*(p^c \cdot A^d), \tag{6}$$

where P is the buying price for the gamble, c and d are the weights of probability and amount, and J^* is a strictly monotonic judgment function.

The contingent weighting theory implies that after transformation to additivity, ratings can be expressed

$$\log(J^{-1}(R)) = a \cdot \log(p) + b \cdot \log(A), \tag{7}$$

and prices can be written

$$\log(J^{*-1}(P)) = c \cdot \log(p) + d \cdot \log(A). \tag{8}$$

This model implies that the additive components for probability in the rating task $(a \cdot \log(p))$ are linearly related to those in the pricing task $(c \cdot \log(p))$. Likewise, additive components for amount in the rating task $(b \cdot \log(A))$ should be linearly related those in the pricing task $(d \cdot \log(A))$. This form of contingent weighting implies that the two sets of additive components for each variable should not only be linearly related to each other but should also be linearly related to the logs of the physical values. However, the present tests are more general and do not require the use of physical values.

Mean ratings and mean pricings were transformed to additivity while maintaining the rank order of the data using Kruskal and Carmone's (1969) MONANOVA. Stress, the square root of the proportion of variance unaccounted for by the additive model, ranged from 0.05 to 6.45% in the four tasks. Although Tversky *et al.* (1988) assumed that the weighting functions were power functions, this analysis fits a generalization of the contingent weighting theory that permits subjective probability and utility to be any functions of their physical values. The left and the right panels of Fig. 7 show the additive components from the two tasks for utilities and subjective probabilities. Since the data from the two contexts were so similar after transformation to additivity, averages of the transformed ratings and averages of the transformed prices are presented in Fig. 7. In

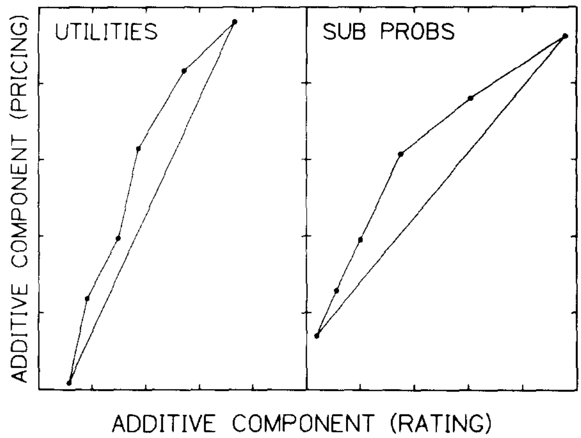

FIG. 7. Estimates of utilities on the left and subjective probabilities on the right, assuming the additive model for both tasks. Additive components from the pricing task are plotted against those from the rating task. According to contingent weighting theory, the curves should be linear; change-of-process theory implies that they should be logarithmic.

both panels, the additive components are concave downward, inconsistent with contingent weighting theory.

Change-of-process theory attributes rank order shifts to different underlying processes across tasks. Probabilities and payoffs are assumed to be combined multiplicatively in the pricing tasks and additively in the rating tasks. Furthermore, utilities and subjective probabilities are assumed to be constant across response modes. Attractiveness ratings can be expressed

$$R = J(c \cdot s + u), \tag{9}$$

where s is the subjective probability, u is the utility of the gamble, J is a strictly monotonic function, and c is a scaling constant that calibrates subjective probabilities along the same scale as utilities. The calibration constant, c, is assumed to be constant across all gambles in both contexts, although it seems likely that c might vary across contexts if the range of monetary amounts were varied.[3] For buying prices, the theory can be written

$$P = J^*(s \cdot u), \tag{10}$$

where J^* is a strictly monotonic function.

[3] Subjective probabilities are presumably bounded from 0 to 1.0, whereas utilities have no bounds. Without the scaling factor, c, utility could overwhelm the effect of probability if the range of amounts were increased, unless c depends on the range of utilities.

According to change-of-process theory, when ratings are transformed to additivity, they can be expressed

$$J^{-1}(R) = c \cdot s + u, \tag{11}$$

and transformed prices are

$$\log(J^{*-1}(P)) = \log(s) + \log(u), \tag{12}$$

where $J^{-1}(R)$ and $\log(J^{*-1}(P))$ represent the monotonic transformations that render the data parallel. After transformation to additivity, this theory implies that the additive components from the pricing task ($\log(s)$ and $\log(u)$) should be logarithmically related to those in the rating task (s and u). This log relationship should hold for both utilities and subjective probabilities and is consistent with the negatively accelerated curves shown in Fig. 7.

A specific ordinal test between the change-of-process theory and the contingent weighting theory can also be performed. Assume s and u represent the additive scales of subjective probability and utility in the rating task, and s^* and u^* refer to the additive scales of subjective probability and utility in the pricing task. Let $u_1 = 0$, $a = u_2 - u_1$, $b = u_3 - u_2$, $c = u_4 - u_3$, $d = u_5 - u_4$, and $e = u_6 - u_5$ for utilities in the attractiveness rating task. Corresponding differences between utilities are denoted a^* to e^* in the buying prices. Similarly, let differences between subjective probabilities be $s_1 = 0$, $v = s_2 - s_1$, $w = s_3 - s_2$, $x = s_4 - s_3$, $y = s_5 - s_4$, and $z = s_6 - s_5$ in the rating task and v^* to z^* in the pricing task.

Change-of-process theory implies that in this additive decomposition, u^* should be logarithmically related to u, and s^* should be logarithmically related to s. Figure 8 illustrates this relationship using hypothetical values. Differences between hypothetical scale values have a predictable relationship. For example, the left panel of Fig. 8 shows that $a^* > e^*$ (in buying prices) but $a < e$ (in attractiveness ratings). Similarly, in the right panel, $v^* > z^*$ (in prices), but $v < z$ (in ratings).

Contingent weighting theory implies a different order. According to this theory, the additive components across the different tasks should be linearly related. The additive decomposition implies logarithmic scales in which the weights become multipliers [see Eqs. (7) and (8)]. Differences between scale values should have the same rank order in different tasks. That is, if $a^* > e^*$ in buying prices, then $a > e$ in attractiveness ratings. Similarly, if $v^* > z^*$ for buying prices, then $v > z$ in attractiveness ratings.

Figure 9 presents both data and the theoretical representations in terms of scale value differences for attractiveness ratings and buying prices. Numbers in each cell are mean responses from the positively skewed context. Examples of some relevant comparisons are shown with solid

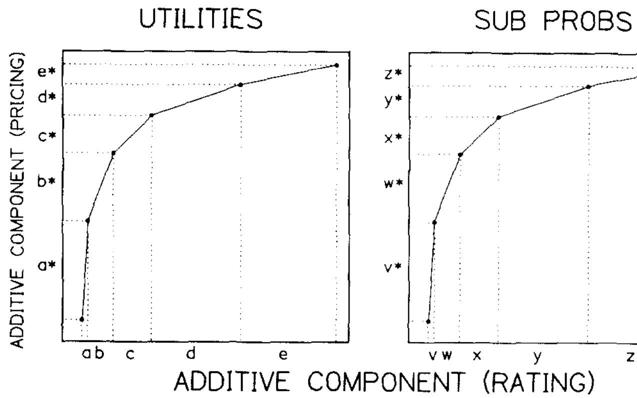

FIG. 8. Hypothetical relationship between additive components for utility and subjective probability from pricing and rating tasks, according to change-of-process theory. The symbols a to e and a^* to e^* represent differences between additive utility scales for ratings and prices, respectively. The symbols v to z and v^* to z^* represent differences between subjective probability scales.

lines for utility differences and dashed lines for subjective probability differences. In the pricing task, $v^* + w^* + x^*$ (.85) $< a^* + b^* + v^*$ (.88) and $a^* + b^* + c^* + d^* + e^* + v^*$ (3.90) $< a^* + b^* + c^* + v^* + w^* + x^*$ (3.98), which simplifies to $d^* + e^* < a^* + b^*$. In the rating task, $v + w + x$ (23.03) $> a + b + v$ (20.35) and $a + b + c + d + e + v$ (42.95) $> a + b + c + v + w + x$ (37.98), which simplifies to $d + e > a + b$. Thus, the rank orders of utility differences change across the two tasks in a fashion that is predicted by the change-of-process theory, but is inconsistent with the contingent weighting theory.

Rank orders of subjective probability differences show the same pattern. For example, in the pricing task, a^* (.35) $< v^* + w^*$ (.53) and $v^* + w^* + x^* + y^* + z^*$ (2.03) $< a^* + v^* + w^* + x^* + y^*$ (2.50), which can be simplified to $z^* < v^* + w^*$ (see dashed arrows in Fig. 9). But in the rating task, $a + b$ (16.10) $> v + w$ (13.80) and $v + w + x + y + z$ (54.60) $> a + b + v + w + x + y$ (50.18), which can be simplified to $z > v + w$. Again, the change in rank orders is predicted by change of processing, but is inconsistent with contingent weighting. Similar patterns are also found in ratings and prices from the negatively skewed context.

Figure 10 presents another way to illustrate this test between the two theories using empirically derived indifference curves. Numbers represent preference orders for gambles in the buying price task (Fig. 10A) and the rating task (Fig. 10B). Probabilities of winning and amounts to win are spaced according to the additive components derived from MONANOVA for the buying price task from Fig. 7. Since the transformation to additivity was successful, this spacing results in parallel and linear indiffer-

Attractiveness Order

	U1	U2	U3	U4	U5	U6
S1	8.45 (0)	12.43 (a)	16.10 $(a+b)$	22.78 $(a+b+c)$	28.12 $(a+b+c+d)$	41.83 $(a+b+c+d+e)$
S2	10.28 (v)	14.85 $(a+v)$	20.35 $(a+b+v)$	26.70 $(a+b+c+v)$	33.50 $(a+b+c+d+v)$	42.95 $(a+b+c+d+e+v)$
S3	13.80 $(v+w)$	18.68 $(a+v+w)$	23.95 $(a+b+v+w)$	31.30 $(a+b+c+v+w)$	39.33 $(a+b+c+d+v+w)$	45.08 $(a+b+c+d+e+v+w)$
S4	23.03 $(v+w+x)$	25.65 $(a+v+w+x)$	35.72 $(a+b+v+w+x)$	37.98 $(a+b+c+v+w+x)$	44.53 $(a+b+c+d+v+w+x)$	52.65 $(a+b+c+d+e+v+w+x)$
S5	37.10 $(v+w+x+y)$	40.30 $(a+v+w+x+y)$	50.18 $(a+b+v+w+x+y)$	50.98 $(a+b+c+v+w+x+y)$	62.15 $(a+b+c+d+v+w+x+y)$	66.98 $(a+b+c+d+e+v+w+x+y)$
S6	54.60 $(v+w+x+y+z)$	55.93 $(a+v+w+x+y+z)$	64.72 $(a+b+v+w+x+y+z)$	68.12 $(a+b+c+v+w+x+y+z)$	72.33 $(a+b+c+d+v+w+x+y+z)$	79.23 $(a+b+c+d+e+v+w+x+y+z)$

Buying Price Order

	U1	U2	U3	U4	U5	U6
S1	0.26 (0)	0.35 (a^*)	0.65 (a^*+b^*)	1.23 $(a^*+b^*+c^*)$	1.73 $(a^*+b^*+c^*+d^*)$	3.12 $(a^*+b^*+c^*+d^*+e^*)$
S2	0.34 (v^*)	0.56 (a^*+v^*)	0.88 $(a^*+b^*+v^*)$	1.58 $(a^*+b^*+c^*+v^*)$	2.67 $(a^*+b^*+c^*+d^*+v^*)$	3.90 $(a^*+b^*+c^*+d^*+e^*+v^*)$
S3	0.53 (v^*+w^*)	0.76 $(a^*+v^*+w^*)$	1.26 $(a^*+b^*+v^*+w^*)$	2.39 $(a^*+b^*+c^*+v^*+w^*)$	3.98 $(a^*+b^*+c^*+d^*+v^*+w^*)$	7.03 $(a^*+b^*+c^*+d^*+e^*+v^*+w^*)$
S4	0.85 $(v^*+w^*+x^*)$	1.14 $(a^*+v^*+w^*+x^*)$	2.26 $(a^*+b^*+v^*+w^*+x^*)$	3.98 $(a^*+b^*+c^*+v^*+w^*+x^*)$	6.61 $(a^*+b^*+c^*+d^*+v^*+w^*+x^*)$	11.34 $(a^*+b^*+c^*+d^*+e^*+v^*+w^*+x^*)$
S5	1.42 $(v^*+w^*+x^*+y^*)$	2.50 $(a^*+v^*+w^*+x^*+y^*)$	4.47 $(a^*+b^*+v^*+w^*+x^*+y^*)$	7.20 $(a^*+b^*+c^*+v^*+w^*+x^*+y^*)$	11.96 $(a^*+b^*+c^*+d^*+v^*+w^*+x^*+y^*)$	22.15 $(a^*+b^*+c^*+d^*+e^*+v^*+w^*+x^*+y^*)$
S6	2.03 $(v^*+w^*+x^*+y^*+z^*)$	3.75 $(a^*+v^*+w^*+x^*+y^*+z^*)$	6.23 $(a^*+b^*+v^*+w^*+x^*+y^*+z^*)$	11.24 $(a^*+b^*+c^*+v^*+w^*+x^*+y^*+z^*)$	20.37 $(a^*+b^*+c^*+d^*+v^*+w^*+x^*+y^*+z^*)$	36.68 $(a^*+b^*+c^*+d^*+e^*+v^*+w^*+x^*+y^*+z^*)$

FIG. 9. Mean responses and theoretical representations for attractiveness ratings (upper panel) and buying prices (lower panel) from the positively skewed condition. Utility differences are represented by the letters a through e and a^* through e^* for attractiveness ratings and buying prices, respectively. Subjective probability differences are represented by v through z and v^* through z^* for attractiveness ratings and buying prices, respectively. The representation of the psychological worth of a utility and subjective probability combination is the sum of scale value differences. Solid and dashed arrows indicate rank order comparisons consistent with the change-of-process theory.

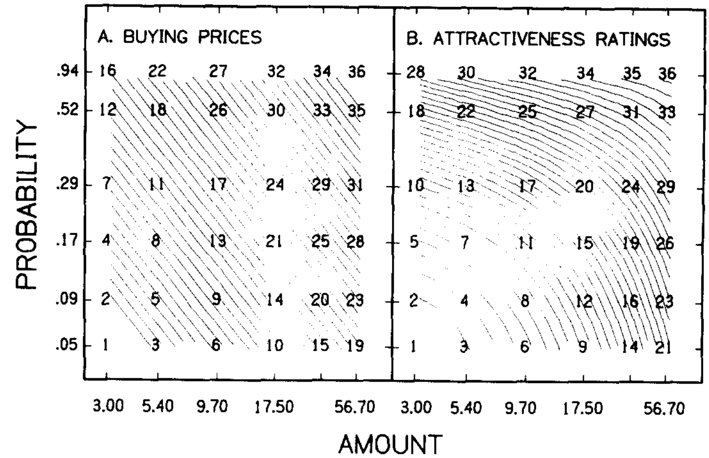

FIG. 10. Empirically-derived indifference curves for buying prices (A) and attractiveness ratings (B). Numbers represent preference orders for gambles with a specified probability of winning and amount to win. The ordinate and abscissa axes are spaced to make the indifference curves for buying prices linear and parallel. Contingent weighting theory implies that indifference curves for attractiveness ratings should be linearly related to those for buying prices. However, the curves are nonlinearly related. The concave-downward shapes are predicted by the change-of-process theory.

ence curves for buying prices. Each curve represents the locus of equal indifference between pairs of successive rank orders (i.e., 1.5, 2.5, 3.5, . . . 35.5).[4]

Contingent weighting theory predicts that both sets of indifference curves should be linear and parallel. Curves for attractiveness ratings should be related to those for buying prices by means of a change in intercept and slope. However, the two sets of indifference curves are nonlinearly related across tasks; no indifference curves can be found for

[4] Empirical indifference curves were fit to buying prices from the positively and negatively skewed conditions using a multiple polynomial regression. The rank orders of gambles were well predicted from polynomial functions of the *sum* of the additive components for s and u (obtained from MONANOVA for buying prices). Predictors included linear and quadratic terms of these sums. The squared multiple correlation was .998. Using the quadratic equation, values of s were computed from combinations of u and rank orders of hypothetical gambles that separated gamble pairs (i.e., 1.5, 2.5, . . .). This method preserved the linearity and parallelism of the indifference curves for buying prices. For attractiveness ratings, rank orders of gambles were predicted from a multiple regression that used the same additive components of s and u for buying prices. Terms included s, u, s^2, u^2, $s \cdot u$, $s \cdot u^2$, $s^2 \cdot u$, and s^2u^2. The multiple correlation was .997. This method allowed nonlinear and nonparallel indifference curves if they were required to fit the data. Once again, using the quadratic equation, values of s were obtained as a function of combinations of u and rank orders of hypothetical gambles that separated gamble pairs.

attractiveness ratings that are linearly related to those for the buying prices. The concave-downward indifference curves in Fig. 10B are predicted by the change-of-process theory.

Fit of change-of-process theory. Change-of-process theory was fit to the mean responses by means of a computer program that solved for parameter estimates to minimize the proportion of residual variance between observations and predictions, $\Sigma(X - \hat{X})^2/\Sigma(X - \bar{X})^2$, summed over the four conditions. Chandler's (1969) STEPIT subroutine was used to perform the minimization. To account for contextual effects in attractiveness ratings, different judgment functions [J in Eq. (9)] were fit for each context assuming range-frequency theory. The model for attractiveness ratings can be written

$$R = a_k\left(w \cdot F_k(\Psi) + (1 - w)\frac{(\Psi - \Psi_o)}{(\Psi_m - \Psi_o)}\right) + b_k\,, \tag{13}$$

where Ψ is the *sum* of utility and subjective probability [argument of J in Eq. (9)], a_k and b_k are constants that depend on the context, $F_k(\Psi)$ is the rank of Ψ in context k, $(\Psi - \Psi_o)/(\Psi_m - \Psi_o)$ is the relative position of the gamble with respect to the endpoints, Ψ_o is the minimum value and Ψ_m is the maximum value, and w is the weight of the frequency component.

For buying prices, the model is expressed

$$P = a_k^* \cdot (\Psi^*)^\alpha + b_k^*, \tag{14}$$

where Ψ^* is the product of the utility and subjective probability [argument of J^* in Eq. (10)], a_k^* and b_k^* are linear constants, and α is an exponent that is assumed to be part of the judgment function. If buying prices were certainty equivalents, α might represent the inverse of the exponent of a power function for utility. Equation (14) represents the function J^* in Eq. (10) as a linear function of a power function.

This change-of-process theory [Eqs. (13) and (14)] was simultaneously fit to the four sets of 36 mean judgments and required 22 parameters: 6 estimated utilities, 5 subjective probabilities (with .94 arbitrarily fixed to its physical value), w, α, 2 values of a_k, b_k, a_k^*, and b_k^* (one for each context), and 1 scaling constant, c, for the subjective probabilities. The proportion of residual variance in the means was 1.4% or less in each of the four tasks. Predictions are shown as dashed lines in the upper and lower panels of Fig. 4. Deviations between the data and the predictions appear to be small and nonsystematic. The estimated utility function was concave downward, and the subjective probability function had a negatively accelerated slope.[5]

[5] Estimated utilities were 1.54, 2.59, 3.99, 5.81, 8.30, and 11.67. Estimates of subjective probabilities were .19, .24, .31, .43, .66, and .94 (.94 was fixed to its physical value). Values

EXPERIMENT 2: CONTEXT AND RESPONSE MODE EFFECTS IN BINARY GAMBLES WITH MIXED OUTCOMES

In Experiment 1, response mode effects were attributed to changing processes; ratings of attractiveness were fit by an additive combination rule, and buying prices were fit by a multiplicative rule. Experiment 2 investigates two additional questions. First, how do the additive and multiplicative processes generalize to more complex gambles? Consider a gamble with some probability of winning A, otherwise a loss of B. One possibility is that with attractiveness ratings, subjects might persist in adding the components. Ratings of attractiveness might be represented

$$R = J_k(c \cdot s + u_A + u_B), \tag{15}$$

where u_A and u_B are the utilities associated with outcomes A and B, s is the subjective weight of the favorable outcome A, c is a scaling constant, and J_k is a judgment function that depends on the context. Buying prices might be represented

$$P = J_k^*(s \cdot u_A + (1 - s) \cdot u_B), \tag{16}$$

where the symbols are defined as above and J_k^* is a judgment function that depends on the context. Note that in Eq. (16), the subjective weight of losing an amount, B, is assumed to be one minus the subjective probability of winning an amount, A. Since A and B are always positive and negative, respectively, Eqs. (15) and (16) allow for sign-dependent weights (i.e., weights that can differ for gains and losses).

The second question addressed in Experiment 2 is whether buying prices for gambles with mixed outcomes depend on the context. Effects of the context due to variations in the distribution of expected values were found in attractiveness ratings but not in buying prices. Perhaps contextual effects in buying prices can be found with more complex gambles.

Method

There were four conditions in Experiment 2 constructed from a 2 × 2 (response mode by context) factorial design. Subjects were asked to either rate the attractiveness of gambles or state their maximum buying prices. In addition, gambles were presented in one of two contexts; the

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of a_k and b_k were 75.85 and 6.16 for the positively skewed context and 72.87 and 1.89 for the negatively skewed context, respectively. Values of a_k^* and b_k^* were .72 and .44 for the positively skewed context and .76 and .23 for the negatively skewed context, respectively. The exponent, α, was 1.64, and the scaling constant, c, was 20.86. The value of w, the estimated weight of the frequency component in Eq. (13), was .10, which suggests that the range component had more influence than the frequency component.

distribution of expected values was either positively or negatively skewed.

Stimuli and design. Gambles were displayed in a format similar to the one shown in Fig. 2. The amount won or lost depended on whether the pointer landed in the black or gray region. All of the gambles had two outcomes, one being a positive amount and the other being a negative amount.

In each condition, there were 60 common gambles constructed from a $4 \times 5 \times 3$ (probability of winning by amount to win by amount to lose) factorial design. The size of the black region in Fig. 2 was varied in proportion to the probability of winning. Levels were .2, .4, .6, and .8. Probabilities of losing (represented by the gray region in Fig. 2) were one minus the probability of winning. Amounts to win were \$5.40, \$9.70, \$17.50, \$31.50, and \$56.70. Amounts to lose were \$1.67, \$5.40, and \$9.70.

Common gambles were embedded in two different contexts. In each context, 121 additional stimuli were included. These stimuli were constructed from an 11×11 (amount to win by amount to lose) factorial design. These contextual stimuli were chosen to create either a negatively or positively skewed distribution of expected value. In the positively skewed context, the probability of winning was always .2. Amounts to win were \$10.30, \$10.90, \$11.50, \$12.10, \$12.70, \$13.30, \$13.90, \$14.50, \$15.10, \$15.70, and \$16.30. Amounts to lose were \$6.10, \$6.40, \$6.90, \$7.00, \$7.30, \$7.60, \$7.90, \$8.20, \$8.50, \$8.80, and \$9.10. In the negatively skewed context, the probability of winning was always .8. Amounts to win were \$39.50, \$42.00, \$43.50, \$45.00, \$46.50, \$48.00, \$49.50, \$51.00, \$52.50, \$54.00, and \$55.50. Amounts to lose were \$1.90, \$2.00, \$2.10, \$2.20, \$2.30, \$2.40, \$2.50, \$2.60, \$2.70, \$2.80, and \$2.90.

Instructions. In the rating tasks, subjects were asked to rate the attractiveness of each gamble using a scale from -80 to 80, where -80 = Very Very Unattractive, -40 = Unattractive, 0 = Neutral, 40 = Attractive, and 80 = Very Very Attractive. Subjects were shown the most attractive and least attractive gambles and were told to make their ratings relative to those extremes using any integer values from -80 to 80.

In the pricing tasks, subjects were asked to consider the maximum amount they would be willing to pay to play the desirable gambles. For the undesirable gambles, subjects were asked to state the maximum amounts they were willing to pay to *avoid* playing the gambles. Subjects always *bought control* of the gamble, either to play it or to avoid playing it. Responses were made in dollars and cents.

Procedure. Subjects completed 15 warm-up trials to familiarize them with the task, the range of the stimuli, and the skewing of the context, followed by 181 experimental trials presented in booklets. There were 18 gambles presented on each page in random order, and page orders were counterbalanced using two latin square designs to create different page orders for each subject. Subjects worked at their own paces and finished in approximately 1 h.

Participants. There were from 40 to 44 different subjects who served in each of the four conditions. A few additional subjects who did not follow instructions were excluded.

Results and Discussion

Response mode effects. Figure 11 shows mean judgments averaged over subjects and amounts to lose for attractiveness ratings (upper panels) and buying prices (lower panels). Data are plotted as a function of amount to win with a separate curve for each probability of winning. Dashed lines show predictions of a model that will be discussed later.

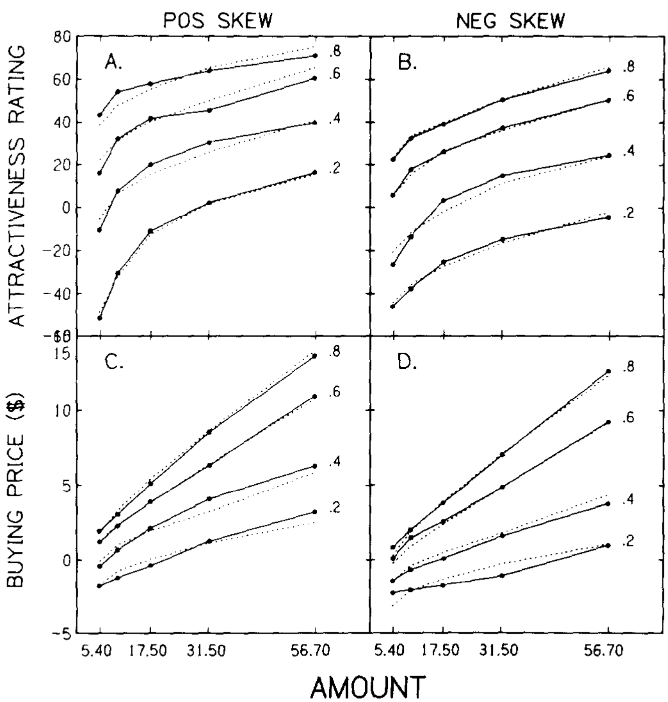

FIG. 11. Mean judgments are plotted as a function of amount to win, with a separate curve for each probability of winning, averaged over amount to lose. Ratings of attractiveness are shown in upper panels; buying prices are shown in lower panels. Left and right panels display results for the positively and negatively skewed contexts, respectively. Dashed lines show predictions. Ratings were fit to an additive model with a range-frequency judgment function; bid were fit to a multiplicative model with a linear transformation of a power function.

For attractiveness ratings, the curves in both of the upper panels appear nearly parallel, consistent with the hypothesis that probability and amount combine additively. Results are similar to those in the upper panels of Fig. 4 from Experiment 1. Graphs of mean judgments (averaged over subjects and amounts to win) plotted against amount to lose with a separate curve for each probability of losing show similar parallel curves for both contexts. Experiment 2 suggests that the parallelism of probability and amount for attractiveness ratings does not hinge on the second outcome being zero, as in Experiment 1, but can also occur with mixed outcomes.

The lower panels in Fig. 11 present mean judgments of buying prices as a function of amount to win with a separate curve for each level of probability (averaged over amount to lose). The shapes of the curves differ from those found for ratings, but resemble the interaction found in the lower panels of Fig. 4, from Experiment 1. In both contexts, the curves form divergent fans of probability and amount, consistent with a multiplicative combination rule.

Experiment 2 allows an examination of the interaction between amount to win and amount to lose for both ratings and prices. Figure 12 shows mean judgments averaged over subjects and levels of probability for attractiveness ratings (upper panels) and buying prices (lower panels). Data are plotted as a function of amount to win with a separate curve for each amount to lose. Again, dashed lines show predictions of a model that will be discussed later. Curves in (A) and (B) slightly converge, and curves in (C) and (D) diverge.

Rank order changes across tasks occur at the individual subject level as well. For example, 59% of the subjects rated the gamble ($5.40, .8; −$5.40) as more attractive than the gamble ($56.70, .4; −$5.40), and only 29% gave the opposite order. In contrast, 66% of the subjects reported a higher price for the gamble ($56.70, .4; −$5.40) than for the gamble ($5.40, .8; −$5.40), and 26% gave the opposite order. Thus, changes in the response mode affect individual subject preference orders when gambles have positive and negative outcomes, as well as positive and zero outcomes (Experiment 1).

Figure 13 takes another look at response mode effects by plotting mean attractiveness ratings against mean buying prices for the positively and negatively skewed contexts in the left and right panels, respectively. Curves connect responses to gambles having the same levels or probability. Points do not fall along a single curve (especially in the positively skewed context); instead, rank orders for the same gambles differ across tasks.

Contextual effects. The effects of context on ratings and prices for gambles with mixed outcomes are shown in the left and right panels in

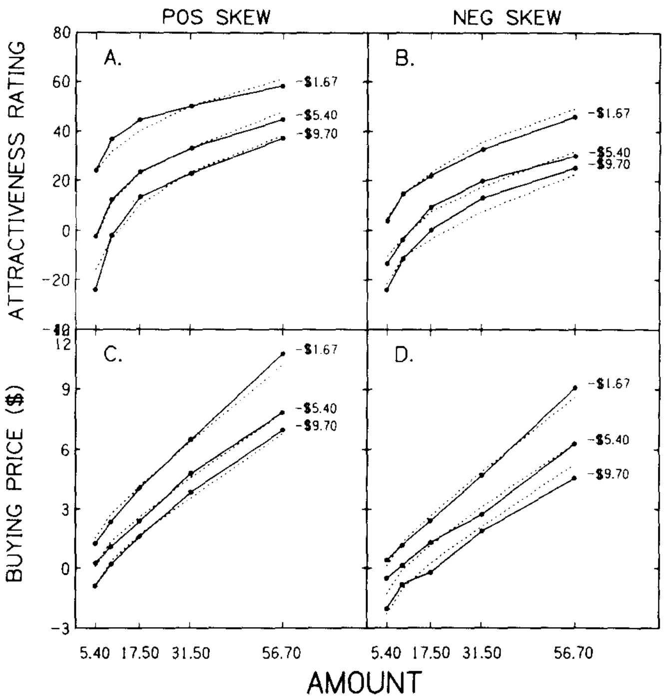

FIG. 12. Mean judgments plotted against amount to win with a separate curve for each level of amount to lose, averaged over probability. Attractiveness ratings and buying prices are shown in the upper and lower panels, respectively. Left and right panels show data from the positively and negatively skewed contexts. Dashed lines are predictions for the theory as shown in Fig. 11.

Fig. 14. Mean responses to common gambles from the positively skewed context are plotted against those from the negatively skewed context, with a separate curve for each level of probability. In both tasks, data points are above the identity line; in the positively skewed context, common gambles have higher attractiveness ratings and higher buying prices than in the negatively skewed context. Attractiveness ratings for the common gambles are, on average, 14 points higher in the positively skewed context than the same gambles in the negatively skewed context. Buying prices for common gambles are, on average, $1.46 higher in the positively skewed context than the same gambles in the negatively skewed context. Attractiveness ratings for gambles from the positively skewed context are concave downward relative to those from the negatively skewed context, as found earlier with the gambles in Experiment 1 (Fig. 5). This concave-downward relationship is predicted by range-frequency theory.

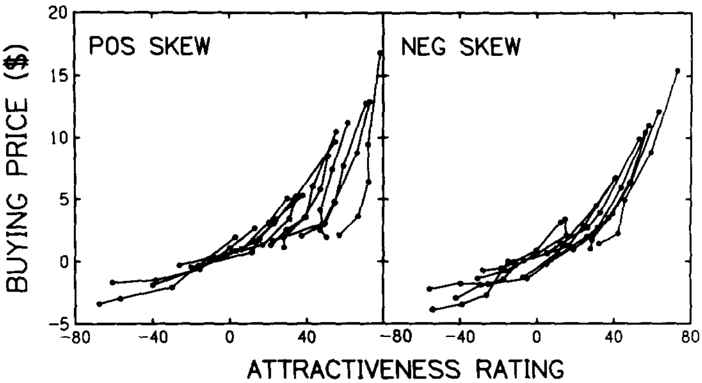

FIG. 13. Mean buying prices plotted as a function of attractiveness ratings for the common gambles in Experiment 2, with a separate curve for each probability of winning. Left and right panels show data from the positively and negatively skewed contexts, respectively.

In Experiment 1, contextual effects in prices were minimal for binary gambles when one outcome was zero. However, contextual effects in prices are more pronounced in Experiment 2 with mixed outcome gambles. Poulton (1989) stated that previous research has not demonstrated contextual effects with monetary responses. The present results show that monetary responses are also sensitive to contextual effects due to skewing of the stimulus distribution of expected values. Perhaps when the gambles become more complex, subjects are more likely to be influenced by contextual manipulations.

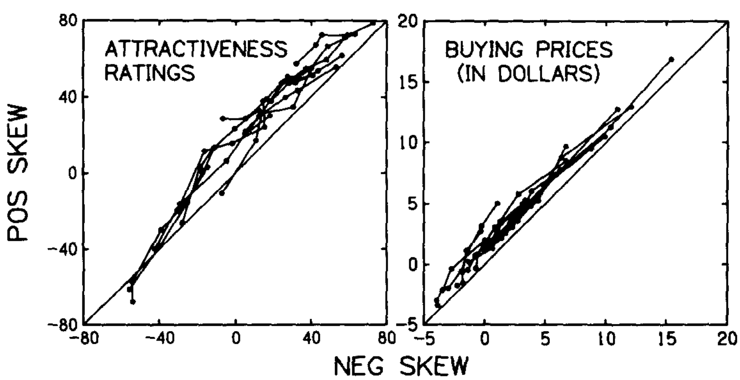

FIG. 14. Mean ratings of attractiveness (on the left) from the positively skewed condition plotted as a function of negatively skewed mean ratings, with a separate point for each gamble common to both conditions. Curves connect gambles with the same probability. In the right panel, mean buying prices from the positively skewed context are plotted against those from the negatively skewed context.

Fit of the Change-of-Process Theory

A special case of Eq. (15) was fit to the data in the rating task as follows,

$$R = a_k\left(w \cdot F_k(\Psi) + (1 - w)\frac{(\Psi - \Psi_o)}{(\Psi_m - \Psi_o)}\right) + b_k\ , \qquad (17)$$

where $\Psi = c \cdot s + u_A + u_B$, and the judgment function is assumed to follow range-frequency theory. The buying price data were fit to a special case of Eq. (16) as follows,

$$P = a_k^*(\Psi^*)^\alpha + b_k^*, \qquad (18)$$

where J_k^* in Eq. (16) is approximated by a linear transformation of a power function that depends on the context, and $\Psi^* = s \cdot u_A + (1 - s) \cdot u_B$. As in Experiment 1, utilities (u) and subjective probabilities (s) were assumed to be the same in both tasks [Eqs. (15) and (16)]. These equations imply that responses between the two contexts should be monotonically related within a task, but responses will differ systematically across tasks. In each panel of Fig. 14, the data deviate from a single curve, but in both cases, the patterns of deviations do not appear systematic. The model required a total of 21 estimated parameters: 7 utilities for wins and losses (with the utility of \$5.40 fixed to its physical value), 3 subjective probabilities (with .8 fixed), one parameter each for w, c, and α, and two parameters for a_k^*, b_k^*, a_k, and b_k, one for each context.

Predictions of the theory are shown as dashed lines in Figs. 11 and 12, averaged over the third factor. The dashed lines fall close to the solid lines; deviations do not appear systematic. The average percentage of residual variance was 2.46% (over tasks and contexts).[6]

EXPERIMENT 3: TESTS OF THE ADDITIVE MODEL FOR ATTRACTIVENESS RATINGS

Results of Experiments 1 and 2 were consistent with the change-of-process theory, which asserts that subjects combine probabilities and

[6] Estimated utilities were −22.87, −17.34, −7.60, 5.40, 10.60, 15.30, 21.46, and 30.14, with 5.40 being fixed at its physical value. Estimated probabilities were .40, .56, .71, and .80, with .80 being fixed to its physical value. The estimated values of a_k and b_k for the additive model were 163.39 and −71.62, respectively, for the positively skewed condition and 171.61 and −55.38, respectively, for the negatively skewed condition. The a_k^* and b_k^* values for buying prices were .19 and 1.41, respectively, for the positively skewed condition and .19 and −.01, respectively, for the negatively skewed condition. The scaling constant, c, was 93.63, and the value for α was 1.38. The estimated weight of the frequency component was .33.

payoffs additively in the rating tasks and multiplicatively in the pricing tasks. However, the additive model has implausible implications across a wider realm of gambles. For example, the additive model implies that if subjects were shown a set of gambles with varying probabilities of winning a zero amount, otherwise zero, the attractiveness of the gambles should increase as the probability of winning zero increases. It is doubtful that this prediction would be supported empirically. Similarly, the additive model implies that if subjects were shown a set of gambles with a zero probability of winning varying amounts, the attractiveness of the gambles should increase as the amount to win increases. This prediction also seems unlikely.

The simplicity of the designs in Experiments 1 and 2 may have contributed to the success of the additive model. Attractiveness ratings increase monotonically with amount to win and probability of winning. Since there were no values of zero probability or zero amount in either experiment, and each factor in Experiment 2 had amounts that were always positive or always negative, subjects may not have confronted the problems inherent in the additive model.

If subjects are presented with gambles for which there is some probability of winning an amount, otherwise zero, in the context of an experiment that includes other gambles with some chance of losing an amount, otherwise zero, they might tend to adopt a multiplicative strategy. Problems with the additive model may become more apparent by the stimuli presented for judgment. This conjecture is explored in the first condition of Experiment 3. A second condition pushes this idea one step further by including gambles with varying probabilities of winning zero and near zero amounts.

Method

There were two conditions in Experiment 3 with different subjects serving in each. In both conditions, subjects were asked to rate the attractiveness (or unattractiveness) of gambles in which there was some probability, p, of winning (or losing) an amount, A, otherwise zero. The distributions of expected values were symmetric about zero in both conditions.

Stimuli and design. Gambles were displayed as in Experiment 1. In the first condition, there were 72 gambles, half with amounts to win and half with amounts to lose. Each of the two sets was constructed from a 6×12 (probability by amount) factorial design. Probabilities were .05, .09, .17, .29, .52, and .94. Amounts were −\$56.70, −\$31.50, −\$17.50, −\$9.70, −\$5.40, −\$3.00, \$3.00, \$5.40, \$9.70, \$17.50, \$31.50, and \$56.70.

In the second condition, additional levels of amount and probability were added to the existing 6 × 12 design. A 7 × 19 (probability × amount) design was created by including a probability level of .025 and amounts of −$1.50, −$.50, −$.30, $0, $.30, $.50, and $1.50. These new amount and probability levels were chosen to be either near zero or at zero. The inclusion of such levels might cause subjects to switch to a multiplicative strategy, rather than use an additive strategy.

Instructions. Subjects were asked to rate the attractiveness of the gambles on a scale from −80 to 80, where −80 = Very Very Unattractive, −40 = Unattractive, 0 = Neutral, 40 = Attractive, and 80 = Very Very Attractive.

Procedure. Subjects completed 10 warm-up trials, followed by either 72 experimental trials (in the first condition) or 133 experimental trials (in the second condition). Stimuli were presented in a random order in booklets with 10 gambles per page. Page order was counterbalanced using two latin square designs.

Participants. There were 49 and 60 subjects who participated in the first and second conditions of the experiment, respectively. Each condition was completed in approximately 45 min.

Results and Discussion

The results of conditions 1 and 2 of Experiment 3 are displayed in Figs. 15 and 16, respectively, which plot mean judgments of attractiveness as a function of the amount to win or lose, with a separate curve for each level of probability. These graphs were plotted separately for each subject, and subjects were grouped according to the appearance of this figure. The upper panel of Fig. 15 displays the results for the subjects whose data appeared nearly parallel for amounts on either side of zero. The vertical separation between the curves is nearly equal for different amounts, and the slopes (for different levels of probabilities) are also nearly equal. Parallel curves can be predicted by an additive model. One could account for the change in rank order of the curves by postulating an additive function of amount and a probability scale that changes sign with the outcome. The lower panel plots the results for subjects whose data appeared divergent; the slopes change for different levels of probability, and the vertical spaces between the curves increase as the amount differs from zero. This intersecting pattern of straight lines is predicted by the multiplicative model.

The panels of Fig. 16, similar to those in Fig. 15, present "parallel" and "divergent" subjects from the second condition. For both groups of subjects, when the amount to win is zero, attractiveness ratings are zero for all levels of probability. However, the groups give quite different responses for amounts that *approach* zero. The percentage of "parallel"

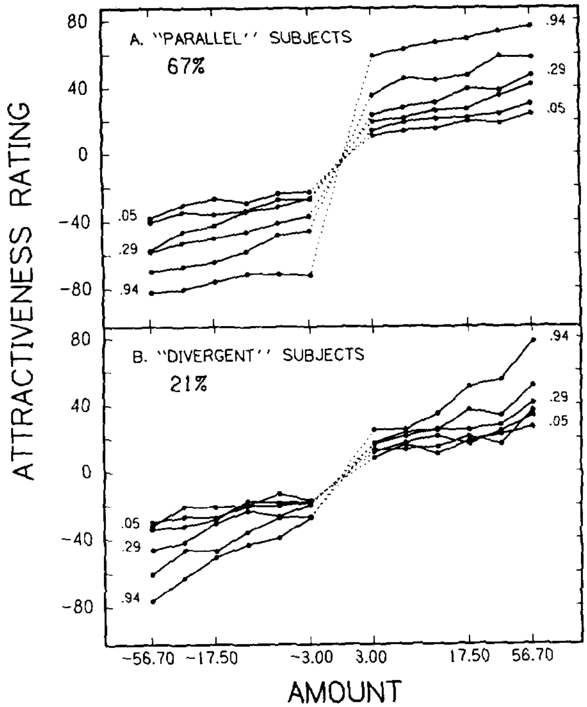

FIG. 15. Mean ratings for the "parallel" subjects (A) and the "divergent" subjects (B) from the first condition of Experiment 3 (with gains and losses, but no zero amounts). Ratings are plotted against values of amount spaced equally on the abscissa. Curves connect gambles with the same probability of winning; the dotted lines show the crossover relationship between the gain and loss curves.

subjects decreased from 67 to 37% from conditions 1 to 2, respectively. By including the additional levels of probability and amount, a smaller percentage of subjects appeared to give responses consistent with an additive process. In addition, more subjects gave "divergent" responses; the percentage of responses that show the bilinear pattern increased from 21 to 63% in conditions 1 vs 2 ($\chi^2_{(1)}$ = 14.5).

Rank orders of the attractiveness rating differ for the "parallel" subjects and the "divergent" subjects, consistent with the theory that subjects use different processes to combine the information. For example, 70% of the "parallel" subjects in the two conditions rated the .94 chance to win $3 as more attractive than the .17 chance to win $56.70, and only 10% gave the opposite order. In comparison, 66% of the "divergent" subjects rated the .17 chance of winning $56.70 as more attractive than the .94 chance of winning $3, and only 22% gave the opposite order. These results suggest that by manipulating the context, i.e., including gambles

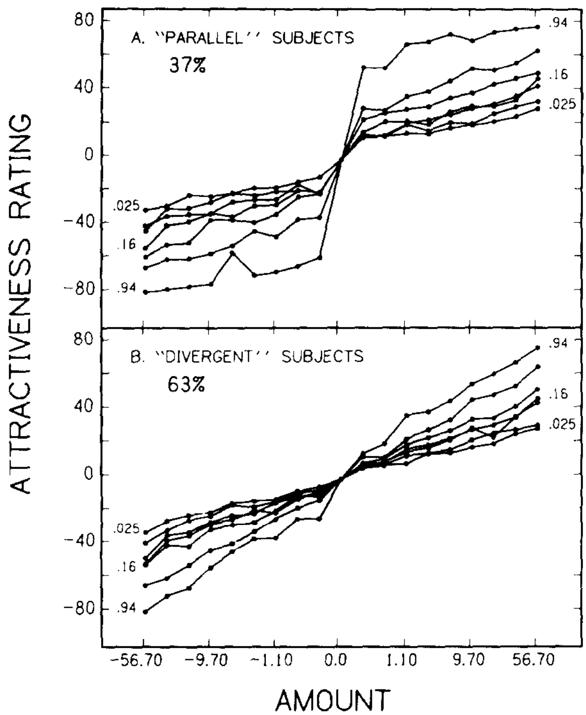

FIG. 16. Mean ratings for the "parallel" subjects and the "divergent" subjects in the second condition of Experiment 3 (with gains, losses, and a zero amount to win). Note that the percentage of "divergent" subjects (63%) is much greater than in the first condition (37%).

with outcomes of zero and negative values, more subjects used a multiplicative combination rule for attractiveness ratings. Problems with an additive model may be more apparent by the stimuli presented for judgment. Thus, the process by which subjects combine information may depend not only on the response mode but also on the context.

Given the interpretation of Experiment 3, it is interesting to conjecture why subjects did not appear to use a multiplicative combination rule for attractiveness ratings in Experiment 2, where gambles also included both losses and gains. Perhaps the answer lies in the design of Experiment 2, which confounded rank, sign, and probability to win; one factor (*A*) was always a gain and the other factor (*B*) was always a loss. Such a design may not force subjects to confront the consequences of an additive model as outcome varies from positive through zero to negative.

DISCUSSION

The present experiments can be summarized as follows:

1. Preference orders differed when elicited by different response modes (attractiveness ratings vs buying prices), consistent with previous research. Results provided tests among three psychological theories of preference reversals. Contingent weighting theory and expression theory were inconsistent with the data, but change-of-process theory could describe the changes in rank order across tasks. Responses to binary gambles with one zero and one positive outcome were consistent with the theory that subjective probabilities and utilities combine multiplicatively for buying prices and additively for attractiveness ratings.

2. The skew of the distribution of expected values did not appear to influence the rank order of the gambles, but did affect the numerical judgments. A gamble with an intermediate expected value was given a *higher* attractiveness rating when the context included a number of gambles with relatively low expected values (positive skew); the same gamble received a *lower* attractiveness rating when the context included additional gambles with higher expected values (negative skew). These contextual effects were attributed to the judgment function and could be predicted by the range-frequency theory. Similar effects also occurred with prices and ratings of binary gambles having mixed outcomes (Experiment 2).

3. When the stimulus context included gambles with (a) near zero values of probabilities and (b) losses, zeros, and gains in the outcomes, the rank order of gambles based on attractiveness ratings was different from the rank order without the additional gambles. Results could be described by assuming the contextual manipulations caused subjects to switch from an additive to a multiplicative combination process. Successive changes in context induced a greater percentage of subjects to change their preference order based on attractiveness ratings to more closely resemble the order obtained with prices. Variations in the response mode *and* the context influenced the rank order in a fashion that could be explained by the change-of-process theory.

Expression Theory and Contingent Weighting Theory

The present study offers direct tests among expression theory, contingent weighting theory, and change-of-process theory. Evidence from the three experiments is consistent with change-of-process theory but creates difficulties for expression theory and contingent weighting theory. Expression theory implies that the points in Fig. 6 should fall on a single monotonic function. Instead, no single curve can describe the relationship between the two sets of deltas. Contingent weighting theory implies that the curves in Fig. 7 should be linearly related. However, both curves are logarithmically related. Neither contingent weighting theory nor expression theory would predict the results in Experiments 2 and 3 without additional assumptions.

Contingent weighting theory addresses a broader behavioral domain than simply preference reversals, and the present data do not address all of its implications. A basic premise of the theory is that the weight of a variable is affected by the "similarity" between the stimulus and the response. There is already considerable evidence that stimulus weight is influenced by the validity, reliability, and diagnosticity of the cue (Birnbaum, 1976; Surber, 1981; Birnbaum & Mellers, 1983), individual beliefs in the validity of the cue (Birnbaum & Stegner, 1981), the believed accuracy of the source (Birnbaum, Wong, & Wong, 1976), and the perceived expertise and bias of the source (Birnbaum & Stegner, 1979), among others. The aspect of contingent weighting theory that is challenged by the present results is the theory that changes in weighting are primarily responsible for reversals of preference between prices and ratings.

It is important to note that the evidence offered for contingent weighting in this situation by Tversky *et al.* (1988) was obtained in an experiment that could not, in principle, distinguish among changes in weight, scale, and process, because levels of probability and amount were confounded. The present study used a factorial design and additional constraints which permitted distinctions among these hypotheses.

It might be argued that the logarithmic relationship in Fig. 7 could be described by a change-of-scale theory. As noted by Tversky *et al.* (1988), contingent weighting can be viewed as a special case of a more general change-of-scale theory, which would make no prediction for Fig. 7. It is possible to distinguish between change of scale and change of process by considering stimulus and response scale convergence (Birnbaum, 1974; Mellers & Birnbaum, 1982) and by testing implications of the theories in a wider realm of experiments. Even this weaker change-of-scale theory faces difficulty.

There are four main arguments favoring change-of-process theory over change-of-scale theory for the present data. First, the logarithmic relationship between the additive scales in Fig. 7 would be considered a coincidence under change-of-scale theory (which would allow any function), but is predicted by change-of-process theory. Second, the judgment functions under change-of-scale theory (which could by any monotonic functions) would just happen to take the appropriate form so that prices form bilinear (multiplicative) fans, ratings are approximately parallel (additive), and contextual manipulations could change the pattern from slight convergence to divergence. Third, contingent weighting theory has not been developed for gambles with mixed outcomes, as in Experiment 2. Results from this experiment were well described by change-of-process theory, using the same scales, which again would be an unexplained coincidence according to change of scale. Fourth, Experiment 3 was designed to explore implications of the change-of-process theory by "steering" subjects away from the additive model. In that experiment, significantly more subjects had a preference order resembling that of prices in Experiment 1. Change-of-scale theory would not predict this contextual effect without additional assumptions. In sum, change-of-process theory provides a better account of the results than contingent weighting or change-of-scale theory.

Other Types of Preference Reversals

The term "preference reversal" is typically used to described changes in preference orders that depend on the method of elicitation. However, it is possible to obtain changes in preference orders using only one dependent variable, as in Experiment 3. Birnbaum *et al.* (1992) found ordinal changes in the values of buying and selling prices of gambles, both of which use estimates of prices as the response mode. When asked "What is the minimum amount you would be willing to accept to sell this gamble?," sellers assigned a higher price to the gamble ($96, .5; $0) than to ($42, .5; $48). Mean selling prices were $48.50 and $44.60, respectively. However, when asked, "What is the maximum amount you would be willing to pay to play this gamble?," buyers assigned a higher price to ($42, .5; $48) than to ($96, .5; $0). Mean buying prices were $40.94 and $32.17, respectively.

These rank order changes cannot be described by contingent weighting since the response mode and probability are held constant. Results are consistent with configural weighting (Birnbaum & Stegner, 1979, 1981; Birnbaum *et al.*, 1992; Mellers, Weiss, & Birnbaum, 1992), which assumes that the weight associated with an outcome depends on its rank among the other outcomes in the gamble. Sellers appear to weight higher-valued outcomes more heavily, whereas buyers appear to place greater importance on lower-valued outcomes (Birnbaum & Sutton, 1992). The models for buying prices [Eqs. (10) and (16)] allow configural weighting since factor A was always the higher-valued outcome and factor B was always the lower-valued outcome. Change-of-process theory does not contradict configural weighting.

In addition to the preference reversals between buying and selling prices, Birnbaum and Sutton (1992) found preference reversals between choices and prices. They showed that prices violate monotonicity: subjects assign a higher price to ($96, .95, $0) than to ($96, .95, $24). However, in direct choice, subjects prefer the dominating gamble. Monotonicity violations have also been obtained by Birnbaum *et al.* (1992) and by Mellers *et al.* (1992) and can be described by an extension of configural weighting.

Contextual Effects

Variations in the distribution of expected values (Experiment 1) changed the numerical values of attractiveness ratings, but did not appear to systematically change their rank order. The interactions between probability and amount were convergent and divergent in the positively and negatively skewed distributions, respectively (Fig. 4). These findings are analogous to those obtained by Mellers and Birnbaum (1983) who asked subjects to assign overall performance ratings to students based on two exam scores. When these distributions (and the distribution of total scores) were positively skewed, the interaction between exam scores was convergent. When the marginal distributions were negatively skewed, the interaction was divergent. That is, students who had one low test score and one high test score received relatively higher performance ratings in the positively skewed condition than in the negatively skewed condition. Rank orders of test score combinations common to both distributions did not vary across contexts.

Mellers and Birnbaum (1982, 1983) found that when subjects combine or compare stimuli along the same dimension, the rank orders of stimulus combinations do not appear to change, and they concluded that contextual effects can be attributed to the judgment function in these situations. However, when subjects combine or compare stimuli along *different* dimensions, the rank orders of stimulus combinations do vary across contexts. These contextual effects can be attributed to the psychophysical functions. Mellers (1982) found that when subjects rated the extent to which hypothetical faculty members were underbenefited or overbenefited based on their salaries and merits, the rank order of judgments of faculty members depended on the distributions of salaries and merits of other faculty. When stimuli from different continua are compared or combined, additional context-dependent transformations (implicit judgments) are theorized to convert dimensions into a common currency for comparison.

In the present paper, context effects produced a new result by altering the rank order of attractiveness ratings in Experiment 3, when additional gambles with zero and negative outcomes were included. The fact that the rank order of two alternatives is influenced by the presence of a third seems analogous to findings in choice (Huber *et al.*, 1982). In the first condition of Experiment 3, when losses were included, approximately one third of the subjects had divergent responses, with order characteristic of a multiplicative model. In the second condition, when zero and near-zero values for probability and amount were also included, roughly twice as many subjects showed this pattern. These findings suggest that both context and response mode can affect the process for combining information. If certain stimuli inform subjects of the undesirable consequences of a combination rule, then their inclusion may influence subjects to use another rule to generate their responses.

Conclusions

The present results suggest that the process by which subjects combine information depends on the task, the stimulus context, and individual difference factors. Data from all three experiments are consistent with the change-of-process theory which accounts for both contextual effects and preference reversals. People appear to use multiple approaches to assess the worth of risky options. According to the present theory, these approaches may lead to inconsistent preferences, but utilities and subjective probabilities appear stable across tasks.

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