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Buying and Selling Prices of Investments: Configural Weight Model of Interactions Predicts Violations of Joint Independence

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Judges evaluated buying and selling prices of hypothetical investments, based on the previous price of each investment and estimates of the investment's future value given by advisors of varied expertise. Effect of a source's estimate varied in proportion to the source's expertise, and it varied inversely with the number and expertise of other sources. There was also a configural effect in which the effect of a source's estimate was affected by the rank order of that source's estimate, in relation to other estimates of the same investment. These interactions were fit with a configural weight averaging model in which buyers and sellers place different weights on estimates of different ranks. This model implies that one can design a new experiment in which there will be different violations of joint independence in different viewpoints. Experiment 2 confirmed patterns of violations of joint independence predicted from the model fit in Experiment 1. Experiment 2 also showed that preference reversals between

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viewpoints can be predicted by the model of Experiment 1. Configural weighting provides a better account of buying and selling prices than either of two models of loss aversion or the theory of anchoring and insufficient adjustment.

Key Words: Anchoring and adjustment; branch independence; buying prices; configural weight theory; contingent valuation; cross-validation; cumulative prospect theory; decision making; endowment effect; interactions; investments; joint independence; loss aversion; point of view; preference reversals; rank- and sign-dependent utility theory; selling prices; uncertainty; utility; willingness-to-accept; willingness-to-pay.

This paper connects two approaches to the study of configural effects in judgment. The first approach is to fit models to data obtained in factorial designs and to examine how well the model describes main effects and interactions in the data. The second approach is to examine violations of ordinal independence properties. Results of these two approaches should be related, if the configural theory is correct, and this study will assess the cross-experiment coherence of the predicted interrelations.

In the typical model fitting study, factorial designs of informational factors are used. Effects termed *configural* appear as interactions between factors that should combine additively according to nonconfigural additive, or parallel-averaging models (Anderson, 1981; Birnbaum, 1973b; 1974; 1976; Birnbaum, Wong, & Wong, 1976; Birnbaum & Stegner, 1979; 1981; Birnbaum & Mellers, 1983; Champagne & Stevenson, 1994; Jagacinski 1995; Lynch, 1979; Shanteau, 1975; Stevenson, Busemeyer, & Naylor, 1991). We use this approach in our first experiment.

In the model-fitting approach, two problems arise as a consequence of possible nonlinearity in the judgment function that maps subjective values to overt responses. The first problem is that nonlinearity in the judgment function might produce interactions that do not represent "real" configurality in the combination of the information (Birnbaum, 1974). The second, related problem is that when nonlinear judgment functions are theorized, models that have quite different psychological implications become equivalent descriptions of a single experiment, requiring new experiments to distinguish rival interpretations (Birnbaum, 1982). Because there are many rival interpretations of the same pattern of interactions, it is unclear if models fit to interactions will predict ordinal tests in a new experiment. A new experiment is usually required, because factorial designs often provide little or no constraint on the ordinal independence properties that distinguish configural from nonconfigural models.

The second approach, used in our second experiment, tests ordinal independence properties that are implied by nonconfigural additive and parallel-averaging models, but which can be violated by configural models. The property tested in this study is *joint independence* (Krantz, Luce, Suppes, & Tversky, 1971). Violations of joint independence cannot be attributed to the judgment function. Joint independence is closely related to a weaker version of Savage's (1954) "sure thing" axiom in decision making, called *restricted branch independence*. Recent papers found violations of restricted branch independence, which refute nonconfigural theories of decision-making in favor of models in which the weights of stimuli depend on the configuration of stimuli presented (Birnbaum, in press; Birnbaum & Beeghley, 1997; Birnbaum & McIntosh, 1996).

In our first experiment, we used the approach of Birnbaum and Stegner (1979) to model judgments of the value of stock investments, based on information concerning the stock's previous price and estimates of its future value made by one or two financial advisors. We then used the configural model and its parameters to design a second study applying the approach of Birnbaum and Beeghley (1997) and Birnbaum and McIntosh (1996) to assess the model's ability to predict violations of joint independence in the second study.

Both interactions and violations of joint independence can be described by configural weight models. However, although both of these phenomena have been demonstrated separately in different judgment domains, we are aware of no study that has used both approaches in the same domain to examine whether the configural weight model fit to interactions in one experiment will successfully predict violations of joint independence in a new experiment. This study will investigate this connection with judgments of the future value of investments.

We use the term *cross-experiment coherence* (CEC) to refer to the analysis of agreement between two different properties of data in two experiments, specified by a model. This predicted connection between experiments is similar to cross-validation, because it connects the relationship between two experiments using a model; however, CEC goes beyond simple cross-validation, because it uses one aspect of data in one experiment (in this case, interactions) to predict a different aspect of data in another experiment (violations of joint independence). The coherence property tested here is the implication of configural weighting that interactions and violations of joint independence are both produced by the same mechanism with the same configural weights and should therefore show the predicted pattern of interconnection.

The concept of coherence can be illustrated by analogy to a mystery novel. In previous chapters we read that a man last seen alive at 9 PM on a rainy night has been found dead, buried in mud beside an old chemical factory at 11 PM. In later chapters, we learned that the butler was seen nearby at 10:30 PM with muddy boots. In this chapter, forensic tests show that the mud on the butler's boots matches the unique soil where the body was found. Returning to judgment research, previous articles have shown interactions and violations of branch independence in separate experiments. In this article, we conduct the specific forensic tests to ask if the particular violations of joint independence and interactions are consistent with the hypothesis that the culprit in both cases is configural weighting.

In order to illuminate the implications of configural weighting, it is useful to first consider a nonconfigural, relative weight averaging model.

Relative Weight Averaging Model

In this study, there were up to two advisors who provided estimates of future value in addition to the price previously paid for a stock. For these variables, a relative weight averaging model can be written as follows:

$$\Psi = \frac{w_0 s_0 + w_P s_P + w_A s_A + w_B s_B}{w_0 + w_P + w_A + w_B} \tag{1a}$$

where Ψ represents the overall impression; s_P, s_A, and s_B represent the subjective scale values produced by price paid (P), and the estimates of future value made by advisors A and B (Estimates A and B); w_P, w_A and w_B represent the weights of price paid and weights due to expertise of advisors A and B, respectively; s_0, and w_0 represent the scale value and weight of the initial impression. If a source is not presented, its weight is assumed to be zero. The initial impression, s_0, represents the impression that would be made on the basis of the instructions and other background information, apart from information specific to the particular investment (Anderson, 1981).

The overt response, R, is assumed to be a monotonic function of the overall impression,

$$R = J(\Psi), \tag{1b}$$

where J is a strictly increasing monotonic function.

Because weights multiply scale values in Expression 1a, the greater the expertise of a source, the greater the impact of that source's message. Because the sum of weights appears in the denominator, the greater the expertise of one source, the less the impact of estimates provided by other sources. Because weights are positive, adding more sources should reduce the impact of the estimate by a given source.

In early applications of the relative weight averaging model, it was assumed that weights are independent of value of the information and of the configuration of other items presented on the same trial. Such models have been termed "additive" (e.g., Anderson, 1962) because they imply no interaction between any two informational factors, holding the number of factors fixed. They have also been termed *constant-weight averaging* models or *parallel-averaging* models (e.g., Anderson, 1981; Birnbaum, 1982) because they imply that the effect of each factor of information should be independent of the values of other factors of information presented.

Configural Weighting

Although the relative weight averaging model often provides a useful first approximation to the data, interactions that constitute apparent evidence against such parallel-averaging models have been observed in a number of studies (Birnbaum, 1972, 1973b, 1974). Such interactions led to differential weight and configural weight models (Anderson, 1981; Birnbaum, 1974, 1982).

In differential weight averaging models, there is a different absolute weight for each value of information on a given dimension, but absolute weights are assumed to be independent of the other values presented. In configural weight models, however, the absolute weight of a stimulus is independent of its value *per se*, but depends on the relationships between the value of that stimulus component and the values of other components also presented (Birnbaum, 1972, 1973b, 1974, 1982; Birnbaum & Sotoodeh, 1991; Champagne & Stevenson, 1994). Research comparing these models has favored configural weighting over differential weighting (Birnbaum, 1973b; Birnbaum & Stegner, 1979; Riskey & Birnbaum, 1974).

Configural weight models have also been applied to judgments of the value of risky gambles, choices between risky gambles, and judgments of the value of goods of uncertain and ambiguous value. The analogy that links these different experimental tasks is as follows: the estimates of the sources of information about an investment or good are analogous to the possible outcomes of a risky gamble, and the expertise of the source of information about an investment or good is analogous to the probability of an outcome in a gamble.

In the field of decision making, where gambles have been a center of attention, there has also been interest in a simple configural weight model, the rank-dependent averaging model, in which the weight of a gamble's outcome is affected by the rank of the outcome among the possible outcomes of a gamble. A number of papers, arising in independent lines of study, have explored models in which the weight of a stimulus component is affected (either entirely or in part) by the rank position of the component among the array of components to be integrated (Birnbaum, 1992; Birnbaum, Coffey, Mellers, & Weiss, 1992; Birnbaum & Sutton, 1992; Chew & Wakker, 1996; Kahneman & Tversky, 1979; Lopes, 1990; Luce, 1992; Luce & Fishburn, 1991, 1995; Luce & Narens, 1985; Miyamoto, 1989; Quiggin, 1982; Riskey & Birnbaum, 1974; Schmeidler, 1989; Tversky & Kahneman, 1992; Wakker, 1993, 1994, 1996; Wakker, Erev, & Weber, 1994; Weber, 1994; Weber, Anderson, & Birnbaum, 1992; Wu & Gonzalez, 1996; Yaari, 1987).

Configural weighting is an additional complication to Equation 1 that allows the weight of a stimulus component to depend on the relationship between that component and the other stimulus components presented on a given trial. Configural weighting can explain interactions between estimates of value, and it can explain preference reversals between judgments in different points of view (Birnbaum & Sutton, 1992; Birnbaum & Stegner, 1979; Birnbaum et al., 1992). Configural weighting can also describe violations of joint (or restricted branch) independence (Birnbaum & McIntosh, 1996; Birnbaum & Beeghley, 1997; Birnbaum & Veira, 1998). Different configural models have different implications for properties such as comonotonic independence, stochastic dominance, distribution independence, and cumulative independence (Birnbaum, 1997, in press; Birnbaum & Chavez, 1997; Birnbaum & McIntosh, 1996; Birnbaum & Navarrete, 1997), but these distinctions will not be explored in this study.

For the model used in the present study, the configural weighting assumptions can be written as follows:

$$w_A = f_V[A, \text{rank}(s_A \text{ in } \{s_P, s_A, s_B\})] \quad (2a)$$

$$w_B = f_V[B, \text{rank}(s_B \text{ in } \{s_P, s_A, s_B\})] \quad (2b)$$

$$w_P = g_V[\text{rank}(s_P \text{ in } \{s_P, s_A, s_B\})] \quad (2c)$$

where the weights are defined as in Equation 1, but they are assumed to depend on the rank of the value of the component relative to the others presented, as well as the expertise of the sources, *A* and *B*, and they are affected by the judge's point of view, *V*.

For example, in Equation 2b, *B* refers to the expertise of Source *B*, and rank(s_B in $\{s_P, s_A, s_B\}$) is either 1, 2, or 3, referring to whether the relative position of the scale value of *B*'s estimate compared to the other stimuli presented for aggregation on that trial is lowest, middle, or highest, respectively. For example, when *B*'s estimate = \$1000, Price = \$1500 and *A*'s estimate = \$1200, then the estimate of \$1000 would have the lowest rank (1); however, the same estimate, \$1000, would have the highest rank (3) when Price = \$500 and *A*'s estimate = \$700. This model assumes that the weight of an estimate depends on the position of its scale value in relation to those of the other estimates describing the same investment; it also depends on the expertise of the source of the estimate.[1]

Point of View, Endowment, Contingent Valuation, and Preference Reversals

According to the theory of Birnbaum and Stegner (1979), configural weights can be altered by changing the judge's point of view (in this case, from seller to buyer). Birnbaum and Stegner (1979) concluded that relatively more weight is placed on lower estimates by buyers compared to sellers. Results compatible with the theory that viewpoint affects configural weighting were found by Birnbaum and Sutton (1992), Birnbaum et al. (1992), Birnbaum and Beeghley (1997), and Birnbaum and Veira (1998). Similarly, Champagne and Stevenson (1994) found that interactions between factors of information used to evaluate employees depend on the purpose of the evaluation. Their results appear to be consistent with the interpretation that "purpose" affects viewpoint and thus affects configural weighting. Birnbaum and Stegner (1981) showed that configural weights can also be used to represent individual differences, and that individual differences in configural weighting can be predicted from judges' self-rated positions.

The theory of the judge's viewpoint can also be used to explain experiments

[1]Because the expertise of *P* was not varied, it is presumed constant, so the variable *P* does not appear in Equation 2c. The weight of this factor might have been manipulated by manipulation of the time since the price was paid. Presumably, the greater the time since the Price was actually paid, the less relevant this information would be to judging its future value. If it were manipulated, then P would appear in Equation 2c, analogous to Equations 2a and 2b.

on the *endowment effect*, also called *contingent valuation* in studies of "willingness to pay" versus "compensation demanded" for either goods or risky gambles (Birnbaum et al., 1992). The literature on the endowment effect, which developed independently of research on the same topic in psychology (e.g., Knetsch & Sinden, 1984), has been largely devoted to showing that the main effect of endowment (i.e., viewpoint) is significant, persists in markets, and is troublesome to classical economic theory (Kahneman, Knetsch, & Thaler, 1991, 1992).

In classical economic theory, the effect of endowment is to change a person's level of wealth, which can produce a very small difference between buying and selling prices. However, the empirical difference between buyer's and seller's prices is too large to be explained by classical economic theory (Harless, 1989). Appendix A presents a brief treatment of the classical, expected utility theory of buying and selling prices of gambles, and it shows the difficulties of that approach to explain the phenomena.

Reviews of the literature on the endowment effect can be found in Kahneman et al. (1991, 1992) and van Dijk and van Knippenberg (1996). Kahneman et al. (1991) suggested that the idea of loss aversion (Kahneman & Tversky, 1979) might account for the difference between selling and buying prices. According to the notion of loss aversion, the buyer considers goods as gains and the buying price as a loss, whereas the seller considers the goods sold as losses and the selling price as a gain. Unfortunately, the idea was not crystalized into a clear theory, and studies in the endowment literature were not designed to test the notion of loss aversion against Birnbaum and Stegner's (1979) configural weighting theory. Appendix B presents two specific models that combine the idea of loss aversion with specific assumptions made in Tversky and Kahneman (1992). As noted in Appendix B, neither of these loss aversion models gives a satisfactory account of buying and selling prices of risky gambles or goods of uncertain value. The general idea of loss aversion is that viewpoint (or endowment) affects the values of the outcomes, rather than the configural weights.

Birnbaum and Stegner (1979) showed how to distinguish the effects of experimental manipulations on weight and scale value. In their model of buying and selling prices, changes in configural weighting cause different rank orders of judgments in different viewpoints, producing reversals of preference (see also Birnbaum & Sutton, 1992). In the Birnbaum and Stegner (1979) *scale-adjustment model*, scale values depend on the perceived bias of the source of the information as well as the judge's point of view.

In the present studies, bias of sources is not manipulated, and we approximate the effects of point of view on scale values for Price and the Estimates (A & B) as linear functions of their actual dollar amounts,

$$s(x) = a_V x + b_V, \tag{3}$$

where $s(x)$ is the subjective scale value; x is the objective, dollar value of the price or estimate; a_V and b_V are linear constants that depend on point of view, V. Our analyses will compare models that assume Equation 3 against more general models in which scale values are different functions of x in each viewpoint.

The goal of the first experiment is to assess the fit of the configural weight averaging model to judgments of the value of hypothetical stocks, to test its ability to describe the difference between buying and selling prices, and to compare its fit to nonconfigural models. The second experiment will test implications of the model and parameters obtained in the first experiment for the ordinal property of joint independence (Krantz et al., 1971), described in the next section.

Joint Independence

Joint independence is a property that is implied by nonconfigural additive or parallel-averaging models; i.e., it is implied by models in which the factors have fixed weights. For example, consider a case in which there are three estimates, x, y, and z, given by three sources, A, B, and C, of fixed expertise. Let $R(x, y, z)$ represent the overall response to this combination of evidence. Joint independence requires the following:

$$R(x, y, z) > R(x', y', z)$$

if and only if (4)

$$R(x, y, z') > R(x', y', z')$$

If the weights in Equation 1a are independent of value and independent of configuration, then Equations 1a–b imply joint independence (Appendix C). However, configural weight models, as in Equations 2a–c, can account for violations of joint independence, as will be illustrated in the introduction to Experiment 2. Because joint independence is a purely ordinal property, it is unaffected by possible nonlinearity in the judgment function. As long as the J function is strictly monotonic, possible nonlinearity of J can neither create nor eliminate violations of joint independence in Expression 4. In addition, if the weights depend on viewpoint, then there can be different violations of joint independence in different viewpoints, producing reversals of preference.

Thus, Experiment 1 has many possible interpretations, one of which is the configural weight model. This study asks whether the configural weight model fit to interactions in Experiment 1 successfully predicts the pattern of violations and satisfactions of joint independence in Experiment 2.

EXPERIMENT 1

Method

Instructions. Judges were instructed to estimate the values of hypothetical stock market investments from the point of view of a seller or a buyer.

Judgments were based on subsets of the following information: Previous Price (P) is the price paid for the stock one month ago. Estimate A and Estimate

B are the predictions for next year's price of the stock, given by investment advisors *A* and *B*, respectively. Expertise *A* and Expertise *B* are the levels of expertise (ability to predict value accurately) of the advisors who provided the estimates.

In the seller's viewpoint, judges were to "give advice to a friend who was considering selling their stock market investments." The task was to judge the "lowest selling price" their friend should accept to sell each investment.

In the buyer's viewpoint, the task was to "advise a friend who was considering buying stock investments," and to judge the "highest buying price" their friend should offer to purchase each investment.[2]

Advisors were described as independent from each other and unbiased (they were described as having no self-interest or connection to either party of the transaction). These sources held one of three levels of expertise: Low, Medium, or High. Expertise was defined in terms of years of experience and percentage of accurate predictions for stock prices during the previous year. The advisor with the Low level of expertise had 1–4 years of experience and accurately predicted stock prices 60% of the time during the past year. The advisor of Medium expertise had 5–10 years with 75% accuracy, and the High expertise advisor had 11 or more years of experience with 90% accuracy.

To illustrate the concepts of "lowest selling price" and "highest buying price," an example was presented involving a necklace worn by the experimenter. Judges were told the original purchase price of the necklace ($50). They were instructed to determine the highest amount they would offer to purchase the necklace (above which they would prefer to keep their money). Next, judges were instructed to imagine they owned it, and to decide on the lowest amount they would accept to sell it (below which they would rather keep the necklace). This example was given in addition to printed instructions similar to those in Birnbaum and Sutton (1992) that described buyer's and seller's viewpoints.

Design. There were 129 experimental combinations generated from the union of three different subdesigns. There were 108 trials produced from a 3 by 3 by 2 by 3 by 2, factorial design of Price paid ($500, $1000, or $1500) by Expertise of source *A* (Low, Medium, or High) by Estimate of source *A* ($700 or $1300) by Expertise of source *B* (Low, Medium, High) by Estimate of source *B* ($800, or $1200).

The second subdesign consisted of 18 trials with information from only one advisor in a 3 by 3 by 2, factorial design of Price ($500, $1000, or $1500) by Expertise *B* (Low, Medium, High) by Estimate *B*($800 or $1200).

Three trials provided only information on Price paid ($500, $1000, or $1500).

[2]Instructions to "advise a friend" are intended to define uniform viewpoints. Instructions to judge the "most *you* would pay" or the "least *you* would accept to sell" invoke the judge's individual situation and presumably would enhance individual differences within a viewpoint. For example, individuals' differing levels of wealth and attitudes toward risk may affect their viewpoints. Such individual differences could be studied using the techniques of Birnbaum and Stegner (1981); however, the purpose of the present study is to compare results between viewpoints and across experiments, so we chose methods intended to reduce individual differences.

Procedure. Judges first received an instruction booklet describing the task and both viewpoints, followed by the presentation on "lowest selling price" and "highest buying price" for the necklace.

Judges were then given their first of two booklets to complete. There was a separate booklet for each viewpoint, which included 15 representative warm-up trials and 129 randomly ordered experimental trials, intermixed from the three subdesigns. Warm-up trials were checked for superficial consistency with instructions before judges proceeded to the experimental task. Six different random orders were created from a Latin-square combination of six page orders. The order of the two tasks was counter balanced across judges: approximately half received either point of view first.

Judges. Judges were 71 undergraduates, who received credit towards one option to fulfill an assignment in Introductory Psychology.

Results

Figure 1 displays the mean judgments for cases in which the information consisted of the estimate of a single advisor (*B*) and Price. Data in all figures are represented by symbols (circles, squares and triangles), and predictions of the configural weight model (discussed in the next section) are shown as lines. Mean judgments in Fig. 1 have been averaged over Judges, Price, and Point of view. They are plotted as a function of source *B*'s Estimate ($800 or $1200), with a separate curve for each level of *B*'s Expertise. The crossover of curves illustrates an interaction between the source's expertise and that source's estimate; the greater the expertise, the greater the effect of the source's estimate (the greater the slope in Fig. 1) Analysis of variance indicated that the interaction between *B*'s Expertise and *B*'s Estimate, was statistically significant, $F(2, 140) = 37.22$ ("significant" denotes $p < .01$ throughout this paper).

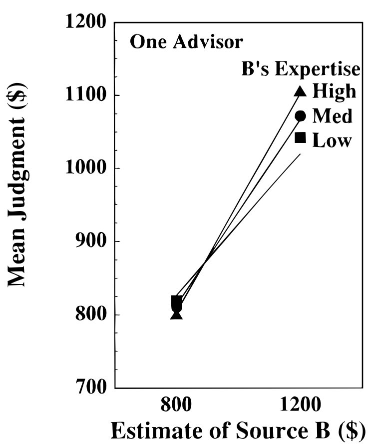

FIG. 1. Mean judgments based on a single advisor (*B*), plotted against *B*'s estimate, with a separate symbol for each level of *B*'s expertise, averaged over Judges, Price paid, and Viewpoint. Filled squares, circles, and triangles represent judgments based on sources of Low, Medium, and High expertise, respectively. In all figures, curves show predictions of configural weight theory (Equations 1–3).

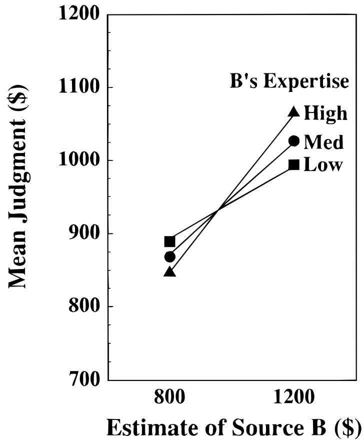

FIG. 2. Mean judgments based on two advisors as a function of Source *B*'s Estimate, with separate symbol and curve for each level of Source *B*'s Expertise, averaged over Judges, Price paid, Viewpoint, Source *A*'s Estimate and Source *A*'s Expertise. Consistent with prediction, slopes in Fig. 2 are less than those in Fig.1.

Figure 2 plots mean judgments from the design with estimates from two advisors as a function of *B*'s estimate with a separate curve for each level of *B*'s expertise, as in Fig. 1, averaged over the estimates and expertise of source *A* as well as over Price and Point of View. Equation 1 correctly predicts that the slopes of the curves (the change in response produced by the same change in the stimulus) should be less in Fig. 2 than in Fig. 1 because in the former case the slopes are proportional to $w_B/(w_0 + w_P + w_B)$, whereas in Fig. 2 the slopes are proportional to $w_B/(w_0 + w_P + w_B + w_A)$. The interaction in Fig. 2 between *B*'s Estimate and *B*'s Expertise, is significant, $F(2, 140) = 133.87$.

Figure 3 plots mean judgments from the two-advisor design as a function of *B*'s estimate, with a separate curve for each level of source *A*'s expertise, averaged over other factors. As predicted by the model of Equation 1, the greater the expertise of source *A*, the less the effect of source *B*'s estimate, because

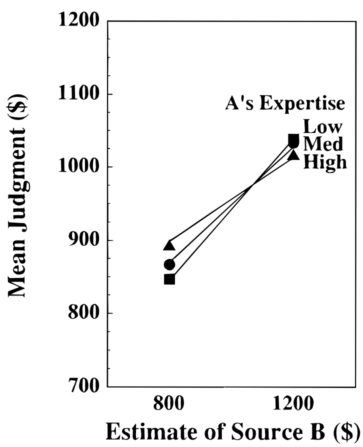

FIG. 3. Mean judgments based on two advisors as a function of Source *B*'s Estimate, with a separate curve for each level of Source *A*'s Expertise, averaged over other factors. In this case, the greater the expertise of source *A*, the less the effect of source *B*'s estimate.

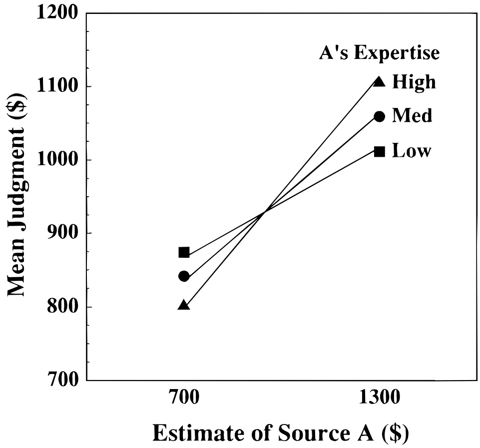

FIG. 4. Mean judgments based on two advisors, as a function of Source *A*'s Estimate with a separate curve for each level of Source *A*'s Expertise averaged over other factors. As in Fig. 2, the effect of a source's estimate varies directly with that source's expertise.

$w_B/(w_0 + w_P + w_A + w_B)$ varies inversely with w_A. This interaction, between *B*'s Estimate and *A*'s Expertise, is significant, $F(2, 140) = 90.23$.

Figures 4 and 5 correspond to Figs. 2 and 3, respectively, except that source *A*'s estimate is plotted on the abscissa (abscissa spacing reflects the wider spread of *A*'s estimates compared to *B*'s). In Fig. 4, the interaction between source *A*'s expertise and *A*'s estimate is shown for the design with two advisors. As in Fig. 2, increasing the expertise of a source increases the effect of that source's estimate; $F(2, 140) = 162.31$. Figure 5 shows that the effect of source *A*'s estimate is decreased by increasing the expertise of source *B*. This inverse crossover replicates the pattern in Fig. 3 and it is also statistically significant, $F(2, 140) = 114.04$. Figures 1–5 replicate previous findings (Birnbaum, 1976; Birnbaum & Mellers, 1983; Birnbaum & Stegner, 1979; 1981; Birnbaum, Wong, & Wong, 1976; Surber, 1981). An exception in the literature is Singh

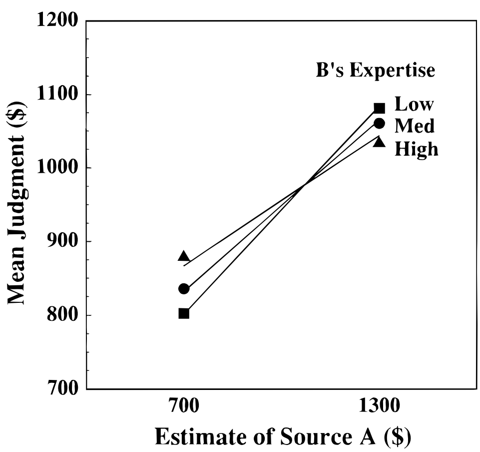

FIG. 5. Mean judgments based on two advisors, as a function of Source *A*'s Estimate with a separate curve for each level of Source *B*'s Expertise, averaged over other factors. As in Fig. 3, the effect of one source's estimate varies inversely with the expertise of the other source.

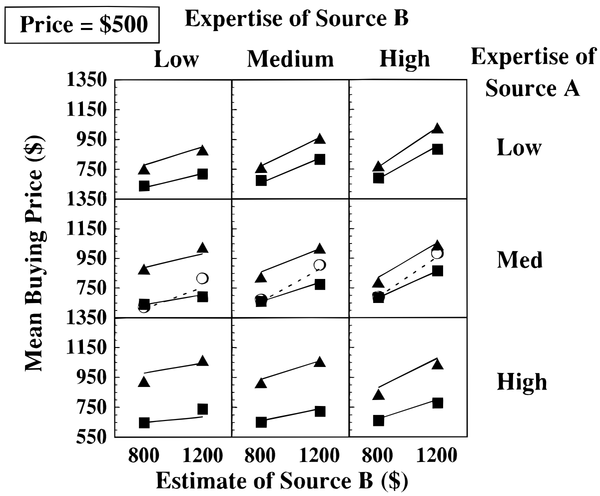

FIG. 6. Mean judgments in the buyer's viewpoint when Price is $500, based on two advisors, (shown as filled squares and triangles for *A*'s estimate = $700 and $1300, respectively), and based on one advisor (shown as open circles). Each panel shows mean judgments plotted as a function of *B*'s Estimate, with a separate curve for each level of *A*'s Estimate. Panels represent different combinations of expertise of Sources *A* and *B*. Solid and dashed curves show predictions of configural weight averaging model (Equations 1–3) for judgments based on two or one advisor(s), respectively.

and Bhargava (1986), who found a nonsignificant interaction between one source's reliability and the other source's message.

Figures 6, 7, and 8 show mean judgments in the buyer's viewpoint for each of the combinations with estimates from two sources, when the price was $500, $1000, and $1500, respectively. In each figure, there are nine panels for each combination of expertise of the two sources; from the left column of panels to the right, the expertise of Source *B* increases from Low to High. The top row, middle row, and bottom row of panels show results when Source *A* is Low,

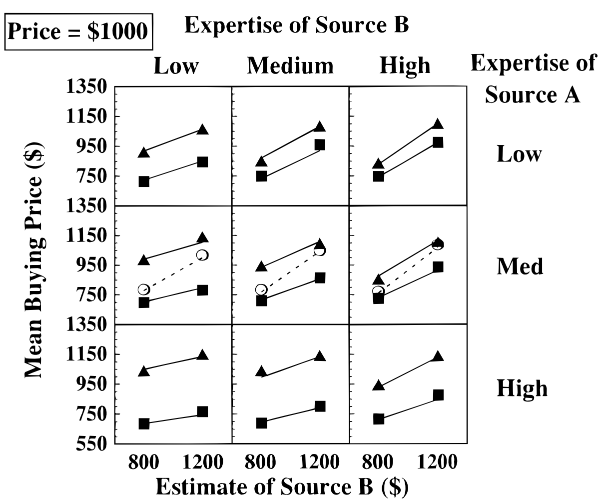

FIG. 7. Mean judgment of buyer's price, as in Fig. 6, except Price = $1000.

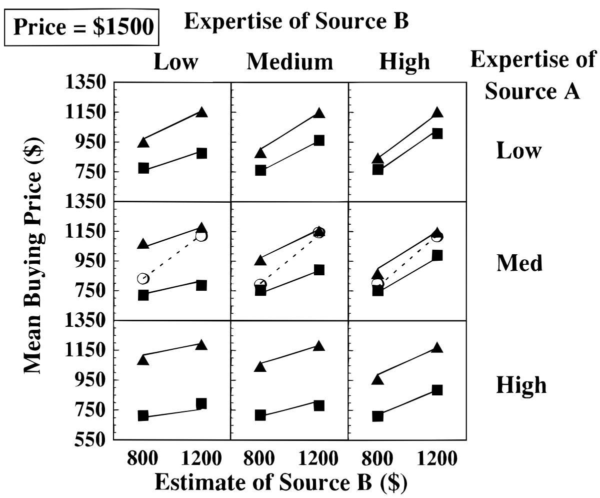

FIG. 8. Mean judgment of buyer's price, as in Fig. 6, except Price = $1500.

Medium, and High in expertise, respectively. Within each panel, mean judgments are plotted against the Estimate of Source *B*, with separate symbols for each level of Estimate of Source *A*; filled squares and triangles represent mean judgments when Source *A*'s estimate was $700 or $1300, respectively. Each point is averaged over 71 judges. Lines in all figures represent predictions of the configural weight averaging model (Equations 1, 2a–c, and 3), described in the next section.

The vertical gaps in each panel of Figs. 6–8 represent the effect of Source *A*'s estimate. If the judges did not attend to Source *A*'s estimate, then there would be no vertical gap between the squares and triangles. Similarly, if judges did not attend to Source *B*'s estimate, then the curves within each panel would be horizontal. Note that the vertical gaps between the curves increase from the top panels to the lower panels in each figure, showing that as the Expertise of Source *A* increases, the effect of Source *A*'s estimate is increased. Similarly, the slopes of the curves within each panel increase from left to right, showing that as the Expertise of Source *B* is increased, the effect of Source *B*'s estimate is increased. As the slopes increase from left to right within each row, notice also that the vertical gaps decrease, consistent with the inverse crossover in Fig. 5. As the Expertise of Source *B* increases, the effect of Source *A*'s estimate decreases. Similarly, as the vertical gaps increase from the top row to the bottom, the slopes decrease, consistent with the inverse effect of *A*'s expertise on the effect of *B*'s estimate (Fig. 3).

The open circles in the middle row of panels in Figs. 6, 7, and 8 show mean judgments for the design in which there is only one source of information (Source *B*), in addition to Price. Dashed lines show the corresponding predictions of the configural weight averaging model. The effect of *B*'s estimate (slope) is greater when there is only one source than when there is also a second source. For any level of expertise of source *B*, the slope is greater for the open circles and dashed lines than for the solid symbols and solid lines.

Figures 9, 10, and 11, show the same information as Figs. 6–8 for the seller's

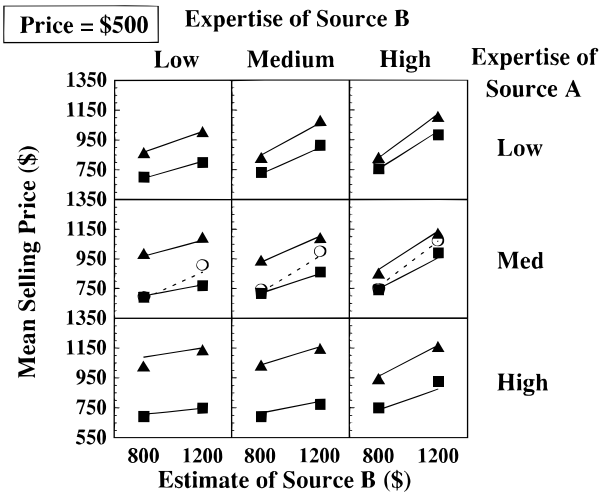

FIG. 9. Mean judgment of seller's price, as in Fig. 6, except Price = $500.

point of view, for prices of $500, $1000, and $1500, respectively. As in Figs. 6–8, the slopes increase directly with *B*'s expertise and decrease with *A*'s expertise; again the vertical gaps increase directly with *A*'s expertise and inversely with *B*'s expertise. Again, the open circles for a single source show steeper slopes than the solid squares or triangles, showing that the effect of source *B*'s estimate is decreased when source *A* also provides an estimate. Seller's judgments are $121 higher on the average than Buyers' judgments of two source combinations ($F(1, 70) = 76.6$).

Within each panel of Figs. 6–11, the curves would be parallel if weights were independent of rank and value. Instead, the curves for the buyer's point of view (Figs. 6–8) show divergence to the right in panels for all values of Price (i.e., the vertical gaps are greater when *B*'s estimate is $1200 than when it is $800 in Figs. 6, 7, and 8). Such divergence is consistent with greater weights

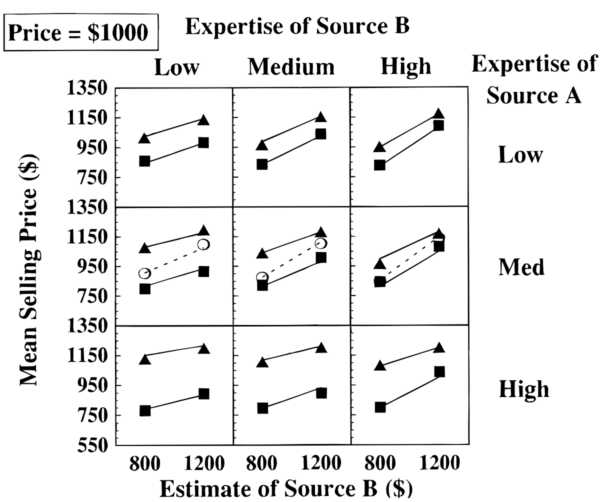

FIG. 10. Mean judgment of seller's price, as in Fig. 6, except Price = $1000. Note that curves within each panel converge to the right.

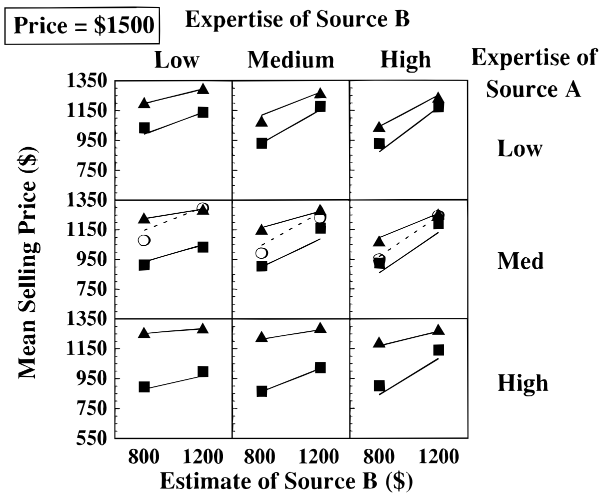

FIG. 11. Mean judgment of seller's price, as in Fig. 6, except Price = $1500. Curves converge to the right in each panel.

on lower estimates. In the seller's point of view, however, the curves within each panel diverge only when the price is $500 (Fig. 9); for prices of $1000 and $1500 (Figs. 10 and 11), the curves converge to the right.

Although the two-way interaction between Estimate *A* by Estimate *B* is nonsignificant when averaged over Price and Viewpoint, $F(1, 70) = 2.26$, the three-way interaction between Price by Estimate *A* by Estimate *B* is significant, $F(2, 140) = 21.99$; furthermore, the three-way interaction of Point of View by Estimate *A* by Estimate *B*, is also significant, $F(1, 70) = 29.31$. The four-way interaction between Point of View by Price by Estimate *A* by Estimate *B* tests the hypothesis that the change in Estimate *A* by Estimate *B* interaction for Sellers (as Price varies from $500 to $1500) is the same as it is for Buyers; this interaction was also significant, $F(2, 140) = 17.91$, indicating that the three-way interaction depends on viewpoint. These nonparallel curves can be explained by configural weighting, and the changes in these interactions can be explained by the assumption that configural weights have different patterns in different points of view.

Figures 9–11 for the seller's viewpoint reveal a shift from divergence to convergence as Price increases, suggesting that the middle ranked item in each combination holds the highest weight among the items presented. In Fig. 9, Price is $500, which is less than either source's estimate. The curves tend to diverge to the right, showing that the weight of the middle item (now lowest of *A*'s and *B*'s estimates) exceeds the weight of the highest item. However, in Fig. 11, Price is $1500, and the curves within each panel converge. The two Estimates from *A* and *B* are now the middle and lower values (i.e. both are less than $1500). Convergence in Fig. 11 thus indicates that the middle estimate has greater weight than the lowest estimate. The graphs for the buyer's point of view show consistent divergence for all prices, suggesting that lower ranked estimates consistently hold greater weight.

Fit of the Model

Predicted values were generated by Equation 1a, subject to the assumptions of Equations 2a–c. As in Equations 2a–c, weights were estimated for each combination of expertise and rank of the source's estimate in each point of view, requiring 9 weights for sources *A* and *B* (3 levels of expertise by 3 levels of rank) and 3 weights for price in each point of view, one for each rank position of Price. When there are two components to be integrated, the model assigns ranks 1 and 3 to the lowest and highest scale values, respectively. When there is only one piece of specified information, its rank is assumed to be 2 (middle level of rank). The weight of any stimulus not presented is assumed to be zero.

The weight of the source of medium expertise who provided a middle estimate was fixed to 1 in both points of view, leaving 11 weights to estimate in each viewpoint. The function, *J*, in Equation 1b was assumed to be linear. The values of a_V and w_0 were assumed to be the same in each point of view, but b_V in Equation 3, and the initial impressions, s_0, were estimated in each point of view, which yields a total of 28 parameters to be estimated from 258 mean judgments.

The model was fit to minimize the following index of fit:

$$L = \sum_{i=1}^{258} \left[\frac{(R_i - \hat{R}_i)}{SE_i} \right]^2 \quad (5)$$

where L is the function of the parameters to be minimized; $\hat{R}_i$ is the predicted judgment calculated from a model using the parameters estimated; R_i is the mean judgment of each combination; and SE_i is the estimated standard error of the mean for the combination [each term is a squared post-hoc t statistic; $t_i = (R_i - \hat{R}_i)/SE_i$ for cell i of the study]. We also fit the data by simply minimizing the sum of squared deviations and found very similar results. The models were fit by means of a special computer program, JACQFIT, that utilized Chandler's (1969) STEPIT subroutine to accomplish the minimizations.

The value of L for this model is 344.8, with a sum of squared deviations of 120,708. The square root of the average squared t is therefore, 1.16; and the square root of the mean squared error from the model is \$21.63. Estimates of the parameters yielded $a_V = 0.945$ in both viewpoints, $b_V = \$53.96$ for the seller's point of view, and $b_V = -\$0.72$ for the buyer's point of view. The weight of the initial impression, $w_0 = .08$. The values of s_0 are \$817.58 and \$713.57 for the seller's and buyer's viewpoints, respectively. The estimated weights of sources are presented in Table 1.

Table 1 shows that sources of greater expertise receive greater weight within either point of view. In the buyer's viewpoint, for any level of expertise, a lower ranked estimate always has greater weight than a higher ranked estimate. However, in the seller's viewpoint, the highest estimate always has more weight than the lowest estimate, but the middle rank always has the greatest weight. This result is consistent with studies of buying and selling prices of gambles, which have also found that sellers place more weight on highest than lowest outcomes and most weight on intermediate outcomes (Birnbaum & Beeghley,

TABLE 1

Estimated Weights of Sources in Experiment 1

	Viewpoint					
	Seller's rank of estimate			Buyer's rank of estimate		
Credibility	1	2	3	1	2	3
Low	0.27	0.45	0.35	0.67	0.46	0.38
Medium	0.57	(1.00)	0.75	1.26	(1.00)	0.84
High	1.04	2.60	1.71	2.48	2.28	1.50
Price	0.33	0.69	0.36	0.50	0.32	0.10

Note: The weight of the source of medium expertise who gives the middle estimate was set to 1 in both points of view. Rank 1 = lowest estimate; rank 3 = highest estimate.

1997; Birnbaum & Veira, 1998). Within each viewpoint, similar effects of rank were observed for the weights of Price as for an advisor. In the seller's viewpoint, the weight of Price Paid is greater than that of a low credibility source; in contrast, buyers place less weight on the Price paid than they do to a low credibility source.

Comparing the data (symbols) against the predictions of the model (lines) in Figures 1–11, it can be seen that the configural weight model does a good job of describing the main effects and interactions in the data.

We also fit a more general model and two special cases of it, in order to compare different models of buying and selling prices. The general model allows different scale values for each physical value in each point of view and also allows different weights for the initial impression in each point of view. This general model fit only slightly better, $L = 313$, despite using 40 parameters. This minimal improvement of fit suggests that the assumption of linear scale values with the same multiplicative coefficient (Equation 3) can be retained for these data; therefore, one need not postulate that scale values change in any nonlinear way in different viewpoints.

Two special cases of this general model, each with 28 parameters were also fit. One version allowed weights to depend on configuration, but they were forced to be independent of point of view. This model is similar to the loss aversion theory of Kahneman, et al. (1991) combined with the assumption that the weighting function for gains and losses are identical (Tversky & Kahneman, 1992), as described in Model 1 of Appendix B. This version fit markedly worse, $L = 562$; this model cannot account for the changing interactions in Figs. 6–11 between the different viewpoints. This loss aversion model (which allows different scale values but the same weights) cannot account for preference reversals between viewpoints.

The second special case of the general model allowed weights to depend on the viewpoint, and also allowed different w_0 weights for different amounts of information (one vs. two vs. three sources), but it required weights to be independent of configuration. This model, also with 28 parameters, fit still worse, $L = 582$. It cannot account for the interactions in any of the panels of Figs. 6–11.

In summary, the model with configural weights that depend on point of view (Table 1) using scale values that are a linear function of money (and a judgment function that is also a linear function of money) appears to fit nearly as well as the general model, and it fits much better than models that omit the dependence of configural weights on the judge's viewpoint.

EXPERIMENT 2

Predicted Violations of Joint Independence

The weights in Table 1 imply that there should be violations of joint independence, and the difference between buyer's and seller's weights indicates that the pattern of violations of joint independence should be different in the two viewpoints. The second experiment will test these implications. It is worth noting that the usual factorial experiment, like our Experiment 1, may have no tests of joint independence (See Appendices C and D). We next show that the model of Experiment 1 does imply that such violations should be observed, if the experiment is properly designed to find them.

For example, consider the case of three estimates provided by three high expertise sources. Let (x, y, z) represent a case in which the estimates are x, y, and z from three sources, and suppose $x < y < z$. Let $S(x, y, z)$ and $B(x, y, z)$ represent the predicted seller's and buyer's prices for such investments, respectively. In the seller's point of view, the weights of the three high expertise sources are 1.04, 2.60, and 1.71 for the lowest, middle, and highest configural weights, respectively. Therefore, the parameters of Table 1 predict violations of joint independence (Expression 4), as follows:

$$S(\$200, \$950, \$1050) = \$843 > S(\$200, \$600, \$1400) = \$789$$

however,

$$S(\$950, \$1050, \$1600) = \$1188 < S(\$600, \$1400, \$1600) = \$1283$$

Thus, the predicted judgments of the configural weight model for the seller's point of view imply a violation of joint independence for these investments.

However, in the buyer's point of view, judgments of these same investments should satisfy joint independence. The weights in the buyer's point of view are 2.48, 2.28, and 1.50, for lowest, middle, and highest, respectively. These weights imply the following:

$$B(\$200, \$950, \$1050) = \$640 > B(\$200, \$600, \$1400) = \$600,$$

and

$$B(\$950, \$1050, \$1600) = \$1074 > B(\$600, \$1400, \$1600) = \$1064,$$

which satisfies Expression 4 in this case. This change in rank order is also a predicted reversal of preference between two points of view for the second pair of investments.

Such a change from violation to satisfaction of joint independence between viewpoints represents a change in rank order of judgments that cannot be explained by a nonconfigural model, such as the relative weight averaging model, even with different scale values in different points of view and even with a different judgment function in each viewpoint. A nonconfigural model cannot violate joint independence, and a strictly monotonic judgment function can neither create nor eliminate violations of this ordinal property. However, this change is predicted by the configural weight averaging model (see Appendix C).

The theory that interactions are due to nonlinearity of the response scale (nonlinearity in the judgment function, J, of Equation 1b) implies that there should be no violations of joint independence in either viewpoint. However, the theory that interactions in Experiment 1 are due to configural weights implies particular violations of joint independence in Experiment 2. Experiment 2 therefore tests not only if violations of joint independence are observed, but also if the particular pattern of violations and nonviolations is compatible with that predicted from the model of the interactions observed in Experiment 1.

Method

The instructions, stimulus displays, and general procedures were virtually identical to those of Experiment 1, except that in Experiment 2, no mention was made of the Price paid for the stocks and there were instead up to three advisors who gave estimates. As in Experiment 1, judges made judgments from both the buyer's and seller's viewpoints. The major differences in the experiments are that there were different judges and different designs, constructed to test specific predictions from the model of Experiment 1.

Design. The trials were constructed from the union of three subdesigns. The first (and chief) subdesign consisted of 60 trials in which there were estimates from three High expertise advisors, (x, y, z). The purpose of Subdesign 1 was to test the predicted pattern of violations of joint independence. This subdesign was a 4 by 5 by 3, z by $(x + y)/2$ by $|x - y|$ factorial design. The 4 levels of z were \$200, \$400, \$1600, and \$1800; the 5 levels of $(x + y)/2$ were \$900, \$950, \$1000, \$1050, and \$1100; and the 3 levels of $|x - y|$ were 100, 400, and 800. The rationale for using the sum $(x + y)$ and the range $(|x - y|)$ as factors is explained in Appendix D.

Subdesigns 2 and 3 were included to allow estimation of the weights of the sources in Experiment 2, and to provide a context of sources with varied levels of Expertise. The second subdesign consisted of 54 trials in which there were estimates from three sources. Source A was always Medium in expertise, and Sources B and C could be either Low, Medium, or High. This subdesign was a 3 by 2 by 3 by 3, Source A's Estimate by (Source B and C's Estimates) by Source B's Expertise by Source C's Expertise, factorial design. The 3 levels of Source A's Estimate were \$400, \$1000, and \$1600; the 2 levels of Source B and

C's Estimates were ($500 and $1500) or ($900 and $1050); the 3 levels of Source *B*'s Expertise were Low, Medium, and High; and the 3 levels of Source *C*'s Expertise were Low, Medium, and High.

The third subdesign consisted of 26 trials with from one to three estimates from a Low expertise, a Medium expertise, and a High expertise source. This subdesign included a 2 by 2 by 2, factorial design of Low's estimate by Medium's estimate by High's estimate, in which the Low's estimates were either $400 or $1600; the Medium's estimates were either $500 or $1500; and the High's estimates were either $600 or $1400. Also included were all possible combinations produced by leaving out one or two of the above sources of information, yielding an additional 12 trials with estimates from two sources and 6 trials with estimates from only one source.

As in Experiment 1, trials were printed in booklets with instructions for both points of view; again, half of the judges performed the two viewpoints in either order.

Judges. The judges were 100 undergraduates, who served as one option toward fulfilling an assignment in introductory psychology.

Results

Cross-validation of predicted rank orders of judgments. To assess the predictive accuracy of the model of Experiment 1, we calculated the predicted rank orders in buyer's and seller's viewpoints in Subdesign 1 of Experiment 2, using the model and parameters from Experiment 1. These predicted rank orders had correlations of .988 and .997 in the buyer's and seller's viewpoints, respectively, with the obtained rank orders in Subdesign 1 of Experiment 2. These correlations represent cross-validations of the models of Experiment 1 to predict the rank orders of mean judgments obtained in a new experiment (Experiment 2).

Although these correlations seem high, such correlations do not necessarily imply that the model's structural predictions are satisfied (Birnbaum, 1973a). More specific model tests are described in the next sections that test the ability of the model to predict preference reversals between viewpoints and to test for the predicted violations and satisfactions of joint independence.

Cross-experiment coherence: Predicted preference reversals. How well can the model predict *changes* in rank order (preference reversals) between the viewpoints? This question imposes a much greater strain on the model than simply to predict the rank order of the data. To address this question, we calculated the *differences* in rank order between buyer's and seller's predictions and the corresponding *differences* in rank order of the judgments. Differences in rank order of the means of Experiment 2 ("preference reversals" between buyer's and seller's judgments) can be predicted from differences in rank order of predictions of the model of Experiment 1, with a Spearman correlation of .833.

Cross-experiment coherence: Predicted violations of joint independence. The next question is to ask how well the model of Experiment 1 predicts violations of joint independence within each viewpoint of Experiment 2. Changes in rank orders between cases of different values of z (violations of joint independence) in Subdesign 1 were calculated for both the data of Experiment 2 and the corresponding predictions of the model of Experiment 1. Because there are 4 levels of z, there are 6 pairs (of z and z') for each of the 15 cells in Subdesign 1 [of (x, y)]. Of these 6 contrasts, 2 are comonotonic, because they do not change the rank order of the estimates ($200 vs. $400 and $1600 vs. $1800), and the other 4 contrasts are noncomonotonic, because the rank order of the estimates is changed. The configural weight model predicts no violations of comonotonic joint independence; however, it does predict violations of noncomonotonic independence.

For comonotonic joint independence, the predicted variances of changes in rank order are 0 in both viewpoints, and the obtained variances were 2.00 and 2.22 in the buyer's and seller's viewpoints, respectively. For the noncomonotonic cases, the predicted variance of changes in rank order were 0.57 and 18.86 in the buyer's and seller's viewpoints, and the obtained variances were 2.75 and 16.07, respectively.

The pooled correlations, predicting violations of joint independence, were .44 and .90 (both significantly positive, $p < .001$) for the buyer's and seller's viewpoints, respectively, pooled over the 90 cells [6 pairs of (z, z') by 15 combinations of (x, y)]. Even in the buyer's viewpoint, where the predicted violations of joint independence are very small, the violations are significantly predictable. In sum, the model of Experiment 1 successfully predicts both the variance and direction of violations of joint independence in the two viewpoints for Subdesign 1. In the next section, we examine specific predictions of the model.

Tests of predicted violations and satisfactions of joint independence. Based on the weights estimated in Experiment 1, the model predicts violations of joint independence in the seller's point of view but *not* in the buyer's point of view, comparing judgments of (x, y, z) against (x', y', z) when $(x + y)/2 = (x' + y')/2$. Comparing situations in which $|x - y| = 100$ versus $|x' - y'| = 800$, there are 5 contrasts for each value of z, and 4 values of z, making 20 such contrasts in each point of view, yielding 40 contrasts overall.

In the buyer's point of view, all 20 contrasts of means (and medians) were in the direction predicted by the model of Experiment 1: holding $x + y$ constant, mean (and median) judgments in all 20 cases decreased as the range ($|x - y|$) increased from $100 to $800.

However, in the seller's point of view, the model predicts violations of joint independence: when z is the lowest estimate, judgments should decrease as range is increased; however, when z is the highest estimate, judgments should increase with increasing range, because the middle estimate has higher weight than the lowest. Data were consistent with these predictions: In all 10 cases when z was lowest ($200 or $400), means (and medians) decrease as range is increased from $100 to $800, and in all 10 cases when z was highest ($1600 or $1800), mean judgments (and medians) *increase* as range is increased. The binomial null hypothesis that these 10 increases and 10 decreases in judgment occur by chance in the seller's viewpoint, assuming each contrast has a probability of 1/2, is 1/2 to the power of 20 (less than 1 in a million). Therefore, this null hypothesis can be rejected in favor of the model that correctly predicted these twenty contrasts before the experiment.

In summary, all 40 of these contrasts in both points of view were in the directions predicted from the configural weight model fit in Experiment 1. Therefore, the weights estimated from interactions in Experiment 1, an experiment that had no tests of joint independence, successfully predicts the pattern of violations and nonviolations of joint independence in a new experiment designed to test the predictions.

Estimation of weights in experiment 2. The model predicts violations of joint independence with its configural weights. The mean judgments in Subdesign 1 of Experiment 2, $R(x, y, z)$, were fit in each viewpoint to the model,

$$R(x, y, z) = w_L x_L + w_M x_M + w_H x_H + c \tag{6}$$

where x_L, x_M, and x_H are the minimum, median, and maximum of (x, y, z), respectively; w_L, w_M, and w_H are the relative configural weights of Lowest, Middle, and Highest ranked estimates ($x_L < x_M < x_H$) of high expertise, respectively, and c is an additive constant. Parameters were estimated separately in each viewpoint. The weights of the three, high expertise sources were estimated from mean judgments of Experiment 2 as follows: .446, .275, and .072 for lowest, middle, and highest ranks in the buyer's viewpoint, and .164, .366, and .286 in the seller's viewpoint, respectively. (Standard errors of the weights are less than .014 in all cases). These weights show the same pattern as estimated in Experiment 1 from interactions.

Weights for individual judges. The model in Equation 6 was also fit separately to each judge's data in Subdesign 1 of each viewpoint. In the buyer's viewpoint, 63 judges assigned the most weight to the lowest estimate (51 of whom had $w_L > w_M > w_H$); 32 assigned the most weight to the middle estimate (20 of whom had $w_M > w_L > w_H$); and only 5 gave the most weight to the highest estimate (of whom 2 gave the least weight to L). In the seller's viewpoint, 43 judges assigned the most weight to the middle estimate (of whom 25 had the order, $w_M > w_H > w_L$); 36 assigned the most weight to the highest estimate (of whom 29 had $w_H > w_M > w_L$); only 21 assigned the most weight to the lowest estimate (of whom 15 gave the least weight to H). In the buyer's viewpoint, 83 of the 100 judges placed more weight on the lowest than the highest estimate, compared with only 39 who did so in the seller's viewpoint. In the buyer's viewpoint, only 35 judges had $w_M > w_L$, whereas 72 had $w_M > w_L$ in the seller's viewpoint. The median correlations, predicting responses for individual judges in this subdesign were .88 in both viewpoints.

Another individual analysis was used to assess the ability of the model to predict the difference between seller's and buyer's prices in the 60 cells of Subdesign 1. Let $B(x, y, z)$ represent the buyer's price in Subdesign 1, and let $S(x, y, z)$ represent the seller's price. For each cell, we calculated $S(x, y, z)$ −

$B(x, y, z)$, and fit this difference using the right side of Equation 6. If an individual were to place relatively more weight on the lower estimate in the buyer's viewpoint and relatively more weight on the higher and middle estimate in the seller's viewpoint, then the weights will be negative, positive, and positive for w_L, w_M, and w_H. The mean weights were −.28, .09, and .22, respectively, all significantly different from zero [t (99) = −8.32, 4.00, and 7.19, respectively]. The median correlation, predicting individual preference reversals between buyer's and seller's prices for the 100 judges using this analysis was .48. (It is important to note that if a judge gave responses that were higher by a fixed amount in the seller's viewpoint than in the buyer's; then this correlation would be zero. Indeed, if seller's prices were any monotonic function of buyer's prices, then there would be no preference reversals, and any analysis attempting to predict them should do no better than chance.)

Fit of the model to experiment 2. Using the same techniques as in Experiment 1, we fit the configural weight model to the data of all designs in Experiment 2. The estimated weights, presented in Table 2, are very similar in pattern to those estimated in Experiment 1. In both viewpoints, w_0 = .11 and a_V = .89; the values of b_V were estimated to be \$11.94 and \$99.34 in the buyer's and seller's viewpoints, respectively. s_0 was fixed to \$0 in the buyer's viewpoint, and was estimated to be \$87.57 for the seller's viewpoint. For Design 1, the value of L was 168.44 over 120 mean judgments, yielding a root mean square t of 1.18. The root mean squared deviation was \$26.17. These values are comparable to those in Experiment 1. However, the results of the other designs did not fit as well on the average, and over all 280 cells, the value of L was 847.86 for this model. In Design 2, for example, the value of L was 352.1 over 108 cells.

The design of Experiment 2, which was intended to test joint independence, may have produced deviations of fit due to a contextual effect. Most trials in Experiment 2 included estimates from three sources (indeed, Subdesign 1, with three High expertise sources, was nearly half of all trials). There were only 6 trials with information from only one source in either viewpoint. In such cases with less information, judged values were lower than predicted in both points of view, as if judges had a lower value of s_0 in this experiment, especially in cases when less information was provided. Allowing different values of the

TABLE 2

Estimated Weights of Sources in Experiment 2

	Viewpoint					
	Seller's rank of estimate			Buyer's rank of estimate		
Credibility	1	2	3	1	2	3
Low	0.47	0.43	0.33	0.74	0.29	0.22
Medium	0.76	(1.00)	0.72	1.26	(1.00)	0.47
High	1.65	3.05	2.39	3.38	2.09	1.21

Note: The weight of the source of medium expertise who gives the middle estimate was set to 1 in both points of view. Rank 1 = lowest estimate; rank 3 = highest estimate.

weight and value of the initial impression improved the fit, but we are dubious whether these more complex models would generalize to an experiment with a different design.

DISCUSSION

Changing Interactions in Experiment 1

Experiment 1 found that interactions between estimates of value can be altered by changing the judge's point of view. These interactions were fit by a configural weight averaging model in which the weights of the estimates depend on the configuration of estimates and the judge's point of view. In the buyer's viewpoint, lower estimates receive greater weight than they do in the seller's point of view. In the seller's viewpoint, middle and higher estimates receive greater weight than they do in the buyer's viewpoint. Configural weighting describes the pattern of interactions in the data, shown in Figs. 1–11.

The configural weight interpretation of our first experiment could be disputed, however, with the following line of reasoning: Suppose that both the scale values of the estimates *and* the judgment functions, J in Equation 1b, change in different viewpoints. Changes in the scale values could account for changes in rank order between viewpoints, as observed by Birnbaum and Stegner (1979), Birnbaum et al. (1992), and Birnbaum and Sutton (1992). According to this argument, nonlinearities in the J functions produce the changing interactions in Figs. 6–11. Although this argument denies the principles of stimulus and response scale convergence (Birnbaum, 1974; Birnbaum & Sutton, 1992), this argument remains consistent with the data of such experiments as our Experiment 1 and that of Birnbaum and Stegner (1979). But it is not consistent with violations of joint independence in Experiment 2.

Violations of Joint Independence in Experiment 2

If the configural weight interpretation is correct, however, then there can be violations of joint independence. Because joint independence refutes even the complex nonconfigural interpretation that allows changing scale values, and because it is a purely ordinal property, it tests the theory that the interactions can be attributed to the judgment function. These tests show that the interactions are real, and cannot be attributed to the judgment functions.

Violation of joint independence is an even stronger refutation than violation of Birnbaum's (1974) *scale-free* test, also called *interval independence* (Birnbaum, Thompson, & Bean, 1997). The scale-free test requires judgments of intervals, and it assumes that judged "differences" in value are a monotonic function of subjective differences or ratios. The test of joint independence makes an even weaker assumption, namely, that judgments are a monotonic function of subjective values.

The test of joint independence, and its cousin in decision-making, branch independence, requires care in planning because it is easy to choose experimental designs in which it is not really tested. Birnbaum and McIntosh (1996) present an analysis showing that the proper experimental design depends on relations between ratios of successive weights and ratios of differences in subjective value (see Appendices C and D). This analysis shows that in order to design a strenuous test of joint independence, one needs to anticipate the scale values and weights of the stimuli.

Cross-Experiment Coherence: Interactions Predict Joint Independence Violations

By estimating the weights and scale values in Experiment 1, we were able to design a test of joint independence for Experiment 2 (Subdesign 1). We then assessed the success of the parameters from Experiment 1 to predict violations and satisfactions of joint independence in Experiment 2. According to the model of Experiment 1, there should be systematic violations of joint independence in the seller's viewpoint, and minimal violations in the buyer's viewpoint. The experiment found that in 40 contrasts of means (or medians), all 40 were in the direction predicted by the model and parameters of Experiment 1, including all 10 out of 10 cases in the seller's viewpoint where the order was predicted to reverse.

The connections tested here between the experiments are stronger than those demonstrated in the usual cross-validation analysis. In a typical cross-validation, one calculates an equation from one set of judgments and uses it to predict a new set of judgments sampled from the same experiment. Such correlations can be high despite serious flaws in the model. This paper described two novel cross-experiment coherence tests that assess how well the model links different phenomena between two studies: predicted preference reversals and predicted violations of joint independence.

Configural weights estimated from interactions in the first experiment were accurate in predicting not only (1) the rank order of the judgments in the two points of view (which corresponds to the usual cross-validation study), but also (2) the *differences* in rank order produced by changing viewpoint (i.e., preference reversals), and (3) the specific and different patterns of violations of joint independence in different viewpoints. These properties were also examined for individual judges, and it was found that conclusions representing the means were also characteristic of the data of individuals.

The success of the configural weight model of Experiment 1 to predict the results of Experiment 2 is a powerful, new result. Although previous studies have shown separately that configural weighting can explain interactions in judgment (e.g., Birnbaum & Stegner, 1979), and that configural weighting can explain violations of joint independence (e.g., Birnbaum & Beeghley, 1997; Birnbaum & Veira, 1998), the predicted connection between these two aspects of data has not previously been tested, to our knowledge. According to the model, a particular pattern of weights implies a particular set of interactions and a specific pattern of violations and satisfactions of joint independence. This study shows that these two aspects of data show the proper connection with each other imposed by the model. In other words, this study demonstrates a successful case of cross-experiment coherence.

Other Interpretations

It appears that rival interpretations are now forced to be quite complicated: for example, one might argue that judgment functions change in different viewpoints (to explain changing interactions), that scale values change in different viewpoints (to explain preference reversals), and that the scale values also change, depending on the configuration of estimates (to explain violations of joint independence). This interpretation violates both stimulus and response scale convergence (Birnbaum, 1974), and it requires configural effects, attributed to the values instead of the weights. Even this complex interpretation, which requires many more parameters than the configural weight model, would not have predicted the results of Experiment 2 from its fit to Experiment 1.

Another complex, rival explanation is that each stimulus value has a different weight, and the entire mapping from stimulus value to weight differs in each point of view. This differential weight model also requires more parameters than configural weighting, and in previous studies has not fit as well as the configural weight model (Birnbaum, 1973b, 1974; Birnbaum & Stegner, 1979; Riskey & Birnbaum, 1974). There are situations in which neutral stimuli (or 0-valued) receive less weight than positive or negative values (Anderson & Birnbaum, 1976; Birnbaum, 1997), but besides such cases, there has not yet appeared evidence to require differential weighting above and beyond configural weighting.

The configural weights estimated in both experiments are similar to each other and they are also similar to the pattern of weights obtained in buyer's and seller's prices for gambles (Birnbaum & Beeghley, 1997; Birnbaum & Veira, 1998). It appears that the evaluation of risky gambles and of uncertain and ambiguous stimuli such as investments or used cars (Birnbaum & Stegner, 1979) follow the same algebra and similar parameters. Sellers place more weight on higher outcomes and less on lower outcomes than do buyers. Our weights show sellers place more weight on the middle estimate, consistent with judgments of gambles, which have shown that sellers place more weight on intermediate outcomes of 3- and 4-outcome gambles than to either extreme outcome (Birnbaum & Beeghley, 1997; Birnbaum & Veira, 1998).

Choices between gambles also appear to be consistent with configural weight models (Birnbaum & McIntosh, 1996; Birnbaum & Chavez, 1997). Tversky and Kahneman (1992) postulated an inverse-S weighting function in which the middle of three equally likely outcomes receives the least weight. However, violations of branch independence in choices between gambles are opposite the predictions of the inverse-S weighting function (Birnbaum & McIntosh, 1996; Birnbaum & Chavez, 1997; Birnbaum & Navarrete, 1997). So too are the violations of branch independence in judgments of gambles from both viewpoints, and the violations of joint independence in the seller's viewpoint.

Violations of joint independence and the weights in Tables 1 and 2 also violate the predictions of a simple anchoring and adjustment theory, described in Appendix E. Anchoring and adjustment is another form of the averaging model (Birnbaum, et al., 1973), so unless the model is further constrained, the term "anchoring and adjustment" is simply one of many metaphors for averaging. This specific anchoring and adjustment model assumes that judges in the buyer's viewpoint anchor on the lowest estimate and that in the seller's viewpoint, they anchor on the highest estimate. In both cases, the weight of the anchors is presumed to exceed the weights of the adjustments, which are assumed to be equal. Although this anchoring and adjustment model can explain that selling prices are higher than buying prices, it predicts the opposite pattern of violations of joint independence from what is observed in our seller's viewpoint (see Appendix E) and in Birnbaum and Beeghley (1997).

Viewpoint versus Endowment Effects

The term "endowment effect" may be a misnomer, because it is not necessary for the judge to actually possess an item to place a higher selling than buying price on it. All that is needed is to ask the judge to take the perspective, or viewpoint of the buyer or seller (Birnbaum & Stegner, 1979). Also, the term "endowment" limits discussion to two cases: ownership or not, whereas the concept of viewpoint is more general, applying to other examples such as the viewpoints of the plaintiff or defendant in a lawsuit, management versus labor in contract negotiations, republican versus democrat in the evaluations of persuasive speeches, or environmentalist or industry lobbyist in judgments of the regulation of emissions by factories. The concept of viewpoint also permits a continuum of viewpoints rather than just two.

Birnbaum and Stegner (1979) theorized that the judge's viewpoint is affected by the relative costs of overestimating or underestimating, in the same way that differential payoffs in signal detection experiments for hits and false alarms affect decision criteria in that paradigm. The concept of viewpoint admits a continuum of viewpoints, intermediate to and more extreme than those of buyer and seller. For example, when judges are asked to judge the "true value" or "fair price" of used cars or gambles, they give estimates intermediate between those of the buyer and seller (Birnbaum & Stegner, 1979; Birnbaum et al., 1992). Similarly, judges might be asked to take the perspective of a "very cautious buyer" or a "very venturesome seller," which should create new viewpoints more extreme than those of the buyer and seller defined in this study. Within the configural weight model, changes in viewpoint should affect the configural weights of estimates at different ranks; there is no reason that configural weights should not be affected in a nearly continuous fashion by instructions that continuously change the relative costs of over or underestimation.

As noted by Birnbaum and Veira (1998), the finding that most weight is placed on the middle of several estimates in the seller's viewpoint is compatible with scoring rules in certain sports, such as diving, where the combined result is intended to be a "fair" representation of opinions from several experts. In these sports, both highest and lowest scores are disgarded before averaging the others, giving most weight to the middle estimate. We suspect that our college student judges have more experience buying than selling, and therefore find it easier to identify with the buyer's perspective; therefore, their perspective in the seller's viewpoint is closer to the buyer than it might be for other groups. If our judges were storeowners (or perhaps even students asked to identify with storeowners), we anticipate that their configural weights would be shifted to placing most weight on the highest estimate.

In our first experiment, we found that sellers place relatively more weight on Price Paid than do buyers (Table 1). From the buyer's perspective, price paid has a weight that is less than that of the low expertise source for any rank, though it is greater than zero. However, the seller assigns weight to price greater than or equal that of the low expertise source. Apparently, the seller considers price paid to be more important than does the buyer, perhaps because price paid is a "sunk" cost to the seller. For the seller, the price paid represents a potential loss or profit, whereas to the buyer it is merely a piece of information that may have some partial correlation with the future price, with the sources' estimates partialled out.

The theory that configural weighting depends on viewpoint leads to the prediction that manipulation of the costs of over- and underestimation should produce continuous changes in the pattern of configural weights. This theory has the testable implication that the scale values (utility functions) are linearly related between viewpoints.

Loss Aversion versus Configural Weighting

Within the endowment literature, the notion of loss aversion has been used as an intuitive explanation of the difference between buyer's and seller's prices (Kahneman, 1992; Kahneman et al., 1991). However, it appears that when that notion is translated into specific models, it leads to predictions that are not consistent with well-established findings (Appendix B). One model of the loss aversion notion leads to the prediction that there should be no preference reversals between buying and selling prices, and the other model implies that the sum of buying and selling prices should be independent of the range, contrary to results of Birnbaum and Stegner (1979), Birnbaum and Sutton (1992), Birnbaum and Beeghley (1997), Birnbaum et al. (1992), Birnbaum and Veira (1998), and the present data. Combining the second model of loss aversion with the model of Tversky and Kahneman (1992) implies that violations of joint independence should have been observed in both viewpoints opposite to the pattern we observe in the seller's viewpoint (See Appendix B).

The configural weight model explains preference reversals between viewpoints, and predicts that the ratio of selling price to buying price will not be constant, but instead will depend on the range of outcomes. The limiting case of range is when the range of outcomes is zero, as in sure cash. In this case of zero range, the configural weight model implies no change of rank order due to viewpoint.

Buying and selling of goods of uncertain or ambiguous value (such as used cars, investments, or mugs) can also be explained by the configural weight model using the theory that such goods produce internal distributions of values that are known to the judge (Birnbaum, et al., 1992). For example, from experience, an investment predicted by an advisor to be "worth $1000" at some future date may be reasoned by the judge to be of unknown value, with a subjective probability distribution. Not all investments predicted to be worth $1000 will sell for exactly $1000. Therefore, the scale value for an estimate of $1000 is itself the result of the evaluation of an internal distribution. Similarly, the future utility of purchasing a mug is an uncertain investment, as is the purchase of a used car. Even though the car or the mug is received as a sure gain in exchange for cash, the car might break down, and the mug might end up in the back of the cabinet.

The notion that "losses loom larger" than gains, used in the loss aversion notion, may sound similar to the loss function interpretation of Birnbaum and Stegner (1979) that a judge's point of view produces asymmetric costs for overestimation or underestimation; however, the mathematics of changing the reference level (changing the utility function to produce loss aversion) is distinct from the mathematics of the asymmetric loss function. The loss function interpretation, with weighted squared losses, for example, leads to a configural weight model in which weights are affected not only by viewpoint, but also by spacing of the outcomes or estimates as well as their ranks (Birnbaum & McIntosh, 1996, Appendix A). Such a model can even violate comonotonic joint independence, unlike the models of loss aversion.

In our attempts to make the notion of loss aversion into a testable theory, we were unable to develop a model that is compatible with the data. In our opinion, the burden is on those who wish to explain the endowment effect in terms of loss aversion, rather than configural weighting, to specify a theory that can account for well-established findings with buying and selling prices. We are aware of no such theory.

CONCLUDING COMMENTS

According to the configural weight theory, the explanation for the different rank orders of buying and selling prices is that the weights of estimates (or outcomes) of different ranks is changed by changing the judge's point of view. These models assume that the scale values of the estimates (or utilities of the outcomes) are linearly related between viewpoints.

This study was not designed to test among different configural weighting models. The model of Equations 2a–c is a slightly more general model than the Rank-Affected Multiplicative model, which would assume that the weights should be a multiplicative function of expertise and rank (Birnbaum, 1997). Such models imply distribution independence (Birnbaum & Chavez, 1997), a property not tested in this study. For the present study, the weight tax model and the model used here make similar predictions, but based on evidence of Birnbaum and Chavez (1997) with gambles, some version of the model of

Birnbaum and Stegner (1979, Equation 10) may prove superior to the particular form of configural weighting used here when extended to experiments that can distinguish the models.

In conclusion, the configural weight model fit to Experiment 1 predicted that there should be different violations of joint independence in Experiment 2. Experiment 2 was designed to test the implications of the model and parameters of Experiment 1, and the predicted pattern of satisfactions and violations of joint independence was observed. Because the property of joint independence is a purely ordinal property, results confirm that the interactions observed in Experiment 1 are "real" and not attributable to a nonlinear judgment function.

APPENDIX A: CLASSICAL UTILITY THEORY OF BUYING AND SELLING PRICES

In Expected Utility (EU) theory, it is assumed that decisions are based on final wealth states. A person should be willing to pay B to buy gamble G, if the expected utility of the decision to buy exceeds the expected utility of the decision not to buy. Let W represent a person's current total wealth, and let $u(W)$ represent the utility function. Gamble $G = (y, p; x, 1 - p)$ represents the binary gamble to win y with probability p and to win x otherwise.

The highest buying price is the maximal value of B for which the following inequality holds:

$$pu(W + y - B) + (1 - p)u(W + x - B) > u(W), \tag{7}$$

where the left side represents the expected utility of purchasing gamble G for price B and the right side, $u(W)$, is the utility of not making the purchase.

Now consider a person who owns gamble G and is deciding whether to sell it or play it. The owner should sell if the expected utility of selling the gamble exceeds the expected utility of keeping it. The lowest selling price is the minimal value of S for which the following inequality holds:

$$u(W + S) > pu(W + y) + (1 - p)u(W + x), \tag{8}$$

where the left side represents the utility of selling the gamble for S and the right side represents the expected utility of keeping and playing the gamble.

When a person's wealth is much greater than the outcomes of the gambles, then most utility functions imply that the effect of viewpoint will be minimal. For example, suppose $u(x) = \log x$. Consider the buying and selling prices of $G = (\$96, .5; \$12, .5)$. Suppose $W = \$100$, then $B = \$45.53$ and $S = \$48.17$. If $W = \$1{,}000$, $B = \$53.11$ and $S = \$53.17$. If a person's total wealth is \$10,000 and the utility function is logarithmic, then $B = \$53.91$ and $S = \$53.92$, so selling prices should exceed buying prices by only 1 cent! For comparison, Birnbaum and Sutton (1992) found that the median $B = \$25$ and median $S = \$50$ for gamble (\$96, .5; \$12, .5). Because classical EU theory implies such small effects of viewpoint, and because of other failures of EU theory to account for empirical choices between gambles, other explanations have been sought.

APPENDIX B: LOSS AVERSION AND REFERENCE LEVEL MODELS OF BUYING AND SELLING PRICES

This appendix develops two models in which the idea of loss aversion is used to represent the effect of viewpoint, sometimes called the endowment effect. These two models are developed by combining verbal statements from Kahneman et al. (1991, 1992) and Tversky and Kahneman (1991) with specific assumptions in Tversky and Kahneman (1992). These models probably do not represent the views of those authors, since they did not propose a specific theory of buying and selling prices (Kahneman, personal communication, November 6, 1997). These models are intended to serve as a starting point for making the notion of loss aversion into testable rival models that can be compared with the configural weight model of Birnbaum and Stegner (1979).

According to Kahneman, et al. (1991, p. 169), "The hypothesis of interest here is that many discrepancies between WTA (willingness to accept = seller's price) and WTP (willingness to pay = buyer's price), far from being a mistake, reflect a genuine effect of reference positions on preferences. . .This effect is a manifestation of loss aversion, the generalization that losses are weighted substantially more than objectively commensurate gains in the evaluation of prospects and trades. . .if a good is evaluated as a loss when it is given up, and as a gain when it is acquired, loss aversion will, on average, induce a higher dollar value for owners than for potential buyers. . ."

Let B = Buyer's price (WTP), S = Seller's price (WTA). Let $u^{-}(x)$ be the utility function for losses, ($x < 0$) and let $u(x)$ represent the utility function for gains ($x \geq 0$). Consider binary gambles, $(y, p; x)$, $|y| > |x|$, which yield y with probability p and otherwise, x.

Let $W(p)$ represent the decumulative weighting function of cumulative prospect theory for gains, and $W^{-}(p)$ represent the cumulative weighting function for losses. The following approximations are presented in Tversky and Kahneman (1992):

$$u^{-}(-x) = -\lambda u(x) \qquad (9)$$

$$W^{-}(p) = W(p) \qquad (10)$$

where λ is the coefficient of loss aversion; if $\lambda > 1$, then losses loom larger than gains; if $\lambda < 1$ then losses would loom smaller. Equation 10 was assumed in original prospect theory (Kahneman & Tversky, 1979), and was reported as a good approximation by Tversky and Kahneman (1992).

Model 1: A Balance of Prices Against Utilities

Suppose in buying prices, a subject compares the negative utility of paying the price against the positive utility of the gamble's outcomes. Presumably, a person would buy if the benefit (the gamble's utility) exceeds the cost (the negative utility of paying B), $U(G) \geq -u^{-}(-B)$, where $U(G)$ is the utility of the gamble. The highest buying price would be the highest price for which the benefits match or exceed the cost. Suppose that when estimating lowest selling price, the judge matches the positive utility of receiving the selling price against the negative utilities of what would have been won if the gamble had been played instead of sold. Thus, this theory (Model 1) assumes that in the buyer's viewpoint, the outcomes of the gamble are gains, but in the seller's viewpoint, the outcomes are losses. Suppose the value of the gambles follows the model of Tversky and Kahneman (1992). We write these assumptions as follows:

$$-u^{-}(-B) = W(p)u(y) + (1 - W(p))u(x) \tag{11}$$

$$u(S) = -[W^{-}(p)u^{-}(-y) + (1 - W^{-}(p))u^{-}(-x)] \tag{12}$$

Substituting from Equations 9 and 10, we have

$$\lambda u(B) = W(p)u(y) + (1 - W(p))u(x)$$

$$u(S) = W(p)\lambda u(y) + (1 - W(p))\lambda u(x)$$

therefore,

$$u(S) = \lambda^2 u(B)$$

Therefore,

$$S = u^{-1}[u(B)\lambda^2] \tag{13}$$

where u^{-1} is the inverse of $u(x)$. Suppose $u(x) = x^{\beta}$, as postulated by Tversky and Kahneman (1992); it follows,

$$S = B(\lambda^2)^{(1/\beta)} \tag{14}$$

If $u(x) = x$ and $\lambda = 2$, then

$$S/B = 4.$$

Table 1 of Kahneman et al. (1991) lists 12 values of the ratio of S/B, with the median between 4.0 and 4.2. The value reported for lottery tickets is 4.0. If $\lambda = 2.25$ and $\beta = .88$, as reported in Tversky and Kahneman (1992), then $S/B = 6.32$.

This theory implies that Selling Prices should be a constant multiple of Buying prices, and therefore, there should be no preference reversals between buying and selling prices. However, such preference reversals were found by Birnbaum and Stegner (1979) for judgments of the value of used cars, by Birnbaum and Sutton (1992) and Birnbaum, et al. (1992) for binary gambles, and for judgments of three-outcome gambles by Birnbaum and Beeghley (1997), and for four-outcome gambles by Birnbaum and Veira (1998). These preference reversals are systematically related to $|x - y|$, as predicted by the configural weight model. In summary, Model 1 of loss aversion does not explain preference reversals produced by the effect of the range of outcomes in at least five articles.

Kahneman (1992) noted that loss aversion theory would imply that the selling price of a $5 bill, for example, should exceed the buying price for the same bill, unless an exception is made in the theory. Therefore, an exception to loss aversion is postulated for exchange goods, such as cash or chips. However, van Dijk and van Knippenberg (1996) found that buying and selling prices of exchange goods also depend on viewpoint, when the value of the exchange goods is uncertain. Thus, the key to the buying versus selling discrepancy is apparently not whether goods are held for use or for sale, but uncertainty. This result is consistent with the configural weight interpretation, which does not need to postulate an exception to account for buying and selling of sure cash amounts, which are gambles with a zero range.

Model 2: Integration of Prices and Prizes

In this second model of loss aversion, it is assumed that the judge integrates the price of a gamble with the prizes of the gamble. It is assumed that the buyer considers that if he/she wins y, then the profit will be $y - B$, and if the gamble yields only x, then the loss will be $x - B$. Similarly, the seller is assumed to consider the sale to be a profit when x occurs, since the profit is $S - x$. It is assumed that the seller considers it a loss when the higher outcome y occurs, because the seller would have been better off to have kept the gamble, so the loss is $S - y$. These assumptions, combined with cumulative prospect theory, can be written as follows:

$$\text{Buy if CPT}(y - B, p; x - B) \geq 0. \tag{15}$$

$$\text{Sell if CPT}(S - y, p; S - x) \geq 0. \tag{16}$$

Where CPT refers to the cumulative prospect value of the gamble in the model of Tversky and Kahneman (1992). Thus, this model allows rank- and sign-dependent configural weighting, but the configural weights are independent of viewpoint.

Consider binary gambles with equally likely outcomes, $(y, .5; x, .5)$, as studied by Birnbaum and Sutton (1992). The highest buying price satisfies the following:

$$W(.5)u(y - B) + W^{-}(.5)u^{-}(x - B) = 0 \tag{17}$$

Substituting from Equation 9,

$$W(.5)u(y - B) = \lambda W^{-}(.5)u(B - x)$$

let $k = W(.5)/(\lambda W^{-}(.5))$, then

$$ku(y - B) = u(B - x)$$
$$u^{-1}[ku(y - B)] = B - x$$

if $u(x) = x^{\beta}$, then

$$(k^{1/\beta})(y - B) = B - x$$

let $C = k^{1/\beta}$

$$Cy - CB = B - x$$
$$B = (Cy + x)/(C + 1) \tag{18}$$

The lowest selling price satisfies the following:

$$W(.5)u(S - x) + W^{-}(.5)u^{-}(S - \mathrm{y}) = 0 \tag{19}$$
$$W(.5)u(S - x) = \lambda W^{-}(.5)u(y - S) \tag{20}$$

with the same definition of k, we have

$$ku(S - x) = u(y - S)$$
$$u^{-1}[ku(S - x)] = y - S$$

Letting C be defined as above,

$$CS - Cx = y - S$$
$$S = (y + Cx)/(1 + C) \tag{21}$$

Now, note that S and B have the opposite configural weights, 1 and C, for the lower or higher outcomes, respectively. The denominators are the same and we can add $S + B$, yielding the following interesting conclusion:

$$S + B = (y + Cx + x + Cy)/(1 + C) = x + y \tag{22}$$

Thus, the sum of buying and selling price of two 50-50 gambles should equal the sum of the outcomes. This sum should be independent of other factors, such as the range, $|x - y|$, as long as $x + y$ is held constant. Note that this conclusion follows for any weighting functions (derivation did not assume Equation 10). In contrast, configural weight theory implies that $S + B$ will in general vary systematically with the range (Birnbaum & Sutton, 1992).

Data of Birnbaum and Sutton (1992) show that $S + B$ varies systematically with the range. For example, the median buying and selling prices of ($48, .5; $60) are $50 and $54, respectively, for a total of $104. However, the median buying and selling prices of ($12, .5; $96) are $25 and $50, respectively, for a total of only $75. Equation 22 implies that both totals should have been $108. (For all 28 gambles with positive outcomes studied by Birnbaum and Sutton (1992), median $B + S$ was less than $x + y$; furthermore, the difference between $B + S - (x + y)$ was correlated with range ($|x - y|$), with a correlation of $-.96$. Therefore, this loss aversion model does not give an adequate account of buying and selling prices of gambles.

When Model 2 is extended to gambles with three equally likely outcomes, the model implies the opposite pattern of violations of branch independence from that observed by Birnbaum and Beeghley (1997). Applied to three equally likely sources, as in the present experiment, Model 2 (combined with the parameters of Tversky & Kahneman, 1992) implies the following violations of joint independence for cases considered in the introduction to Experiment 2:

$$B(\$200, \$950, \$1050) = \$519 < B(\$200, \$600, \$1400) = \$552 \text{ and}$$

$$B(\$950, \$1050, \$1600) = \$1107 > B(\$600, \$1400, \$1600) = \$964.$$

$$S(\$200, \$950, \$1050) = \$854 < S(\$200, \$600, \$1400) = \$986 \text{ and}$$

$$S(\$950, \$1050, \$1600) = \$1360 > S(\$600, \$1400, \$1600) = \$1345.$$

Note that these predicted violations are the same in both viewpoints. In contrast with these predictions, the data show the opposite violation in the seller's viewpoint and they show a satisfaction of joint independence for these judgments in the buyer's viewpoint.

In summary, neither model of loss aversion combined with the CPT model of Tversky and Kahneman (1992) accurately predicts empirical data for buying and selling prices. Luce (1991) developed expressions for buying and selling prices in the context of a rank- and sign-dependent utility theory based on simple assumptions concerning joint receipts, and more complex cases are considered in Luce (1997). The simple case considered by Luce (1991) rules out Equations 9 and 10. Luce (personal communication, November 14, 1997) is currently working to derive the implications of the more complex cases for buying and selling prices.

APPENDIX C: ANALYSIS OF JOINT INDEPENDENCE

Constant Weight Averaging Model Implies Joint Independence

Suppose three sources, A, B, and C, provide estimates of x_A, y_B, and z_C, respectively; let s_A, s_B, and s_C represent the corresponding scale values. Assume Equations 1a and 1b. Suppose the weights are nonconfigural; i.e., that w_A, w_B, and w_C depend entirely on the expertise of the sources and are independent of the values of the estimates and their configuration. Let $R(x_A, y_B, z_C$ represent the overt judgment.

$$\mathrm{R}(x_A, y_B, z_C) > \mathrm{R}(x'_A, y'_B, z_C) \tag{23a}$$

Because J in Equation 1b is strictly monotonic, Equation 23a holds if and only if,

$$\frac{w_0 s_0 + w_A s_A + w_B s_B + w_C s_C}{w_0 + w_A + w_B + w_C} > \frac{w_0 s_0 + w_A s'_A + w_B s'_B + w_C s_C}{w_0 + w_A + w_B + w_C} \tag{23b}$$

Because the denominators are the same positive value, it follows:

$$w_0 s_0 + w_A s_A + w_B s_B + w_C s_C > w_0 s_0 + w_A s'_A + w_B s'_B + w_C s_C.$$

Subtract $w_C s_C$ from both sides and add $w_C s'_C$ to both sides. Now divide both sides by the sum of weights on both sides, which yields,

$$\frac{w_0 s_0 + w_A s_A + w_B s_B + w_C s'_C}{w_0 + w_A + w_B + w_C} > \frac{w_0 s_0 + w_A s'_A + w_B s'_B + w_C s'_C}{w_0 + w_A + w_B + w_C} \tag{24a}$$

which by the strict monotonicity of J is true if and only if

$$R(x_A, y_B, z'_C) > R(x'_A, y'_B, z'_C) \tag{24b}$$

Therefore, the nonconfigural version of Equations 1a–b implies joint independence. In contrast, the configural weight assumptions (Equations 2a–c) predict violations of joint independence.

Configural Weight Model Implies Violations of Joint Independence

Suppose three sources (A, B, and C) provide estimates, as above. Suppose that the judgment is determined by a configural weight model, in which weights depend on the rank order of the scale values, as in Equations 1a–b and 2a–c. Suppose the three sources are equal in expertise (From Equations 2a–c, they are equal in weight except for ranks of their estimates). Suppose that $0 < z < x' < x < y < y' < z'$. Let w_L, w_M, and w_H represent the relative weights of Lowest, Middle, and Highest estimates for this level of expertise, respectively. Then the following pattern of violations of joint independence,

$$R(x_A, y_B, z_C) > R(x'_A, y'_B, z_C) \text{ and } R(x_A, y_B, z'_C) < R(x'_A, y'_B, z'_C) \tag{25a}$$

holds if and only if

$$\frac{w_M}{w_H} > \frac{s_y{}' - s_y}{s_x - s_x{}'} > \frac{w_L}{w_M} \tag{25b}$$

The opposite pattern of violations is as follows,

$$R(x_A, y_B, z_C) < R(x'_A, y'_B, z_C) \text{ and } R(x_A, y_B, z'_C) > R(x'_A, y'_B, z'_C) \tag{26a}$$

holds if and only if

$$\frac{w_M}{w_H} < \frac{s_y' - s_y}{s_x - s_x'} < \frac{w_L}{w_M} \tag{26b}$$

If the ratios of weights are equal, there will be no violations of joint independence as z is changed from lowest to highest. For there to be a violation of joint independence, the ratios of weights must "straddle" the ratio of differences in scale value (see Birnbaum & McIntosh, 1996, for derivations).

For the three high expertise sources, the weights for the seller's point of view from Table 1 satisfy Expression 25b, because $2.6/1.71 = 1.52 > 1 > 1.04/2.6 = .4$. Because these values straddle 1, there should be a violation of joint independence in every row of Subdesign 1 of Experiment 2, assuming that scale values are a linear function of monetary estimates. Recall that each row of this subdesign varies $|x - y|$ while holding $x + y$ constant; therefore in each row, the ratio of differences is one $[(y' - y)/(x - x') = 1]$. The ratios of weights for the buyer's viewpoint do not straddle 1 (from Table 1, both ratios exceed 1); therefore, there should not be a violation within any row of Subdesign 1 in the buyer's viewpoint.

APPENDIX D: RATIONALE FOR RANGE MANIPULATION

The rationale of using $x + y$ and $|x - y|$ as factors lies in the connection between two ways of writing an averaging model with configural weights that depend on rank (see Birnbaum, 1974, p. 559; Birnbaum & Stegner, 1979, p. 60–61).

For simplicity, consider the case of three equally credible sources, and assume that scale values are equal to physical values. Suppose $z < x, y$. Then the range form of the configural weight averaging model can be written as follows:

$$R(z, x, y) = w_L z + \kappa(x + y) + \omega|x - y| \tag{27}$$

when $x > y$, $|x - y| = x - y$; therefore, this expression becomes:

$$R(z, x, y) = w_L z + (\kappa + \omega)x + (\kappa - \omega)y \tag{27a}$$

which is equivalent to

$$R(z, x, y) = w_L z + w_M y + w_H x \tag{27b}$$

where $w_M = \kappa - \omega$ and $w_H = \kappa + \omega$ are the relative weights of the middle and highest estimates, respectively. It is also useful to note that $\kappa = (w_M + w_H)/2$ and $\omega = (w_H - w_M)/2$.

Alternately, when $x < y$, then $|x - y| = y - x$, so Equation 27 becomes

$$R(z, x, y) = w_L z + (\kappa - \omega)x + (\kappa + \omega)y \tag{28}$$

which is also equivalent to Expression 27, with the same configural weights, except the middle and higher outcomes are x and y instead of y and x, respectively.

When $z > x, y$, then the derivations would be the same, except the term ω would then be proportional to the difference in weights between the middle and lowest ranks. Therefore, if configural weights of the lowest, middle, and highest ranks are not equal and if these differences are affected by viewpoint, it should be possible to detect these effects by examining the effect of the range of outcomes, holding total constant.

APPENDIX E: ANCHORING AND ADJUSTMENT THEORY

This section develops a model in which the buyer is assumed to anchor on the lowest outcome and the seller anchors on the highest outcome. An averaging model can also be written as an anchoring and adjustment model (e.g., Birnbaum et al., 1973, Equations 2 and 3). For simplicity, consider judgments of investments based on two equally credible sources (or gambles with two equally likely outcomes), x and y. Suppose,

$$R(x, y) = \frac{w_A s_x + w_B s_y}{w_A + w_B} \tag{29}$$

let

$$w'_B = \frac{w_B}{w_A + w_B}$$

and

$$w'_A = \frac{w_A}{w_A + w_B} = 1 - w'_B$$

then

$$R(x, y) = s_x + w'_B(s_y - s_x) \tag{30}$$

Equation 30 is equivalent to Equation 29, but it is termed the "anchoring and adjustment" version of the averaging model, where the x term is the "anchor" and the weighted difference term represents the "adjustment." Suppose the adjustment term receives less weight than the anchor; i.e., assume that $w' < 1/2$). If buyers anchor on the lowest outcome and if the sellers anchor on the highest outcome, then this anchoring notion gives an intuitive rationale for different configural weighting in different viewpoints.

Consider the anchoring interpretation of judgments based on three, equally credible estimates, $0 < x < y < z$. Suppose the buyer anchors on the lowest estimate, then the averaging model can be written:

$$B(x, y, z) = s_x + w'(s_y - s_x) + w'(s_z - s_x)$$

where x is the anchor and w' is the relative weight of the adjustments. Suppose the seller anchors on the highest estimate, then

$$S(x, y, z) = s_z + w'(s_x - s_z) + w'(s_y - s_z)$$

It follows that the relative weights in the buyer's viewpoint are $1 - 2w'$, w', and w', for Lowest, Middle, and Highest estimates, respectively. Assuming insufficient adjustment (i.e., $1 - 2w' > w'$), the weight of the lowest outcome will be greatest in the buyer's viewpoint, giving the following inequality (compare with Equation 26b in Appendix C):

$$\frac{w_M}{w_H} = 1 < \frac{w_L}{w_M}$$

In the seller's viewpoint, the weights are w', w', and $1 - 2w'$, for Lowest, Middle, and Highest estimates, respectively, yielding the following:

$$\frac{w_M}{w_H} < 1 = \frac{w_L}{w_M}$$

Note that for both buyer's and seller's viewpoints, the expressions satisfy Equation 26b in Appendix C. Therefore, this theory implies the opposite pattern of violations of joint independence from what is observed in Experiment 2, and the ratios among weights are opposite those in Tables 1 and 2. This theory also predicts no interaction between factors representing estimates that are not anchors, contrary to the data of Experiment 1. In summary, the theory of anchoring and insufficient adjustment is not consistent with the data of either experiment.

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