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On Detecting Nonlinear Noncompensatory Judgment Strategies: Comparison of Alternative Regression Models

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We compare the performance of the two models that are usually used to detect nonlinear noncompensatory (NLNC) judgment strategies—Einhorn's (1970) parabolic and hyperbolic models—to two new models: (1) The scatter model (Brannick & Brannick, 1989), which includes, in addition to the linear combination of attribute values, a nonlinear term—the within profile scatter of the attributes; and (2) The "true conjunctive–disjunctive" model (TCD model), which includes additional nonlinear terms associated with the relative values of the attributes. The analyses of 12 empirical datasets indicate that the scatter model is the best NLNC model in terms of model fit. Furthermore, the analyses also indicate that when judgment strategies are relatively homogeneous, the nonlinear terms of the scatter model and the TCD model are most useful measures of NLNC strategies because they are statistically more powerful than model fit-based measures and because they permit the representation of judgment strategies on a conjunctive–disjunctive continuum. The nonlinear term of the scatter model also allows testing for NLNC strategies on the individual level.

Quite often researchers are interested in examining whether judgment deviates from linear-compensatory strategy. Linear-compensatory strategy is a strategy in which judgment is related linearly to attribute values, with attribute weights reflecting attribute importance. While there are many nonlinear noncompensatory (NLNC) strategies that may be followed, research in human judgment has concentrated primarily on two: the *disjunctive* strategy and the *conjunctive* strategy. In a disjunctive strategy people rely primarily on the high attribute(s) and in conjunctive strategy they rely primarily on the low attribute(s).[1]

The regression approach (Slovic & Lichtenstein, 1971) is commonly used to detect NLNC judgment strategies. In this approach, subjects are presented with profiles consisting of a number of informational cues, each cue representing a value on a certain attribute relevant to the judgment, and are required to make judgments of each of the profiles on the basis of these cues. Their judgments are modeled by linear models (models that do not include product terms and no exponents other than one) and by nonlinear models. A better fit of a nonlinear model is assumed to reflect nonlinear noncompensatory judgment strategy.

Four nonlinear models are examined in this paper. The first two models are the parabolic model and the hyperbolic model. These are the models usually used in the regression approach to examine for the existence of NLNC strategies. These models were introduced by Einhorn (1970) because they are likely to give a better fit than the linear model if the true strategy—the strategy used by the subjects—is conjunctive or disjunctive, respectively. The models are represented by the following equations.

The parabolic model

$$\log Y = \sum_{i=1}^{k} b_i \log X_i$$

The hyperbolic model

$$\log Y = -\sum_{i=1}^{k} b_i \log (a_i - X_i),$$

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[1] This description of conjunctive [disjunctive] *judgment* strategy does not rely on the concept of threshold (or cutoff) which is traditionally used to describe conjunctive [disjunctive] choice strategy. However, it is not clear how meaningful is the concept of threshold for continuous decisions such as judgment. The description we use does not rely on the concept of threshold, but still keeps the essence of what is meant by conjunctive [disjunctive] in choice, since in both judgment and choice, the attributes with low [high] values play a major role in the decision. In choice this occurs because of the existence of threshold and in judgment because of the dominance of the attributes whose values are low [high].

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where Y is the judgments, and X_is are the cues (which by convention are scaled to have a nonnegative correlation with the judgment).

The third nonlinear model which is examined in the paper—*the scatter model*—was proposed recently by Brannick and Brannick (1989). The basic form of the model is

$$Y_j = a + \sum_{i=1}^{k} b_i X_{ij} + b_{k+1} \left[\sum_{i=1}^{k} (Z_{ij} - \bar{Z}_j)^2 \right]^{1/2},$$

where Y_j is the judgment of profile j, Z_{ij} is the standardized value of cue i of profile j (the standardization was done across all profiles), and $\bar{Z}_j = \Sigma_{i=i}^{k} Z_{ij}/k$. The last term of the equation is directly proportional to the internal standard deviation of the profile, and therefore a measure for the profile's scatter.[2] Brannick and Brannick offered this model as an alternative to Einhorn's parabolic model, i.e., as a model for conjunctive judgment strategy. However, this model can also serve to model disjunctive strategy and is, therefore, an alternative to the hyperbolic model (Ganzach, in press a). A positive value of b_{k+1} is indicative of a disjunctive strategy, while a negative value is indicative of a conjunctive strategy.[3]

There are two procedures by which this model can be used to test hypotheses concerning reliance on NLNC strategy. First, the standard procedure of comparing its fit to the fit of the linear model can be used; and second, the deviation of the scatter coefficient from zero could be examined. Note that while the first procedure does not provide information about the nature of the NLNC strategy used, the second procedure does provide such information. In addition, as will be discussed later, the latter procedure is statistically more powerful than the former.

[2] Note that the scatter term could be replaced by cross-product and quadratic terms which have a single coefficient. However, using a single term is not only more simple, but is also psychologically more meaningful.

[3] The nonlinear term in the scatter model as presented above is symmetric in regard to the various attributes. Brannick and Brannick (1989) also suggest a version of the scatter model in which attributes weights affect the nonlinear term. To estimate this version of the model one has to first estimate the B_is—the weights of the linear model. Based on these weights one has to estimate Y*—the (standardized) predictions of the linear model. The scatter term is the square route of the weighted average of the attributes deviations from Y*, where the weights are the B_is (p. 100). The intuition behind this model is that it is likely that people tend to deviate from linearity more when the extreme attribute is important rather than unimportant. We chose, however, not to present this model because while it is considerably more complex, its fit to empirical data is not better (and in most cases even worse) than the fit of the simpler version of the scatter model (see also Footnote 5).

The fourth NLNC model examined in this paper can be labeled the True Conjunctive–Disjunctive model (abbreviated as the TCD model). This model is most closely related to our description of conjunctive and disjunctive strategies (see above), since attributes are assigned weights which depend on their *relative value* (i.e. value on a normalized scale-like Z score). Mathematically, the model includes, in addition to the linear combination of attribute values, nonlinear terms associated with the attributes' relative values. For judgment based on two attributes this model is given by:

$$Y = a + b_1X_1 + b_2X_2 + c\max(Z1, Z2),$$

where b_1 and b_2 are nonnegative (by convention the attributes are scaled to have a positive correlation with the judgment) and Z_1 and Z_2 are the standardized values of the cues (across profiles). For a disjunctive strategy c' is positive and for a conjunctive strategy c' is negative.

For judgment based on three and four attributes the TCD model is given, respectively, by:

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + c_1\max(Z1, Z2, Z3) + c_2\min(Z1, Z2, Z3)$$

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + c_1\max(Z1, Z2, Z3, Z4) + c_2\min(Z1, Z2, Z3, Z4)$$

The generalization for judgments based on i attributes where $i > 4$ is as follows. When i is odd, the TCD model includes $i - 1$ nonlinear coefficients. $(i - 1)/2$ of them are associated with the highest attributes: the first with the highest attribute, the second with the second highest attribute, and so on. $(i - 1)/2$ of the coefficients are associated with the lowest attributes. The first with the lowest attribute, the second with the second lowest attribute, and so on. When i is even, the TCD model includes $(i - 2)$ nonlinear coefficients. The $(i - 2)/2$ are associated with the high attributes and $(i - 2)/2$ with the low attributes.[4]

Like the scatter model, the TCD model can be used to test hypotheses concerning reliance on NLNC strategies, both by comparing its fit to the fit of the linear model, and by examining the coefficients of the nonlinear terms. The second method requires some clarification. In the two attribute case, a positive value of the nonlinear coefficient is indicative of a disjunctive strat-

[4] The motivation for this generalization is that generally there are $i - 1$ nonlinear coefficients that need to be estimated (the ith coefficient depends linearly on the rest of the coefficients). When i is even the $(i - 2)/2 + 1$ coefficient need not be estimated, since it is "in between" in regard to disjunctive/conjunctive strategy.

egy and a negative value is indicative of a conjunctive strategy. In the three and four attribute case, the value of $(c_1 - c_2)$ is examined. Since c_1 represents the "excess weight" given to the positive attribute and c_2 the "excess weight" given to the negative attribute, a positive value of this *deviation-coefficient* is indicative of a disjunctive strategy, while a negative value indicates a conjunctive strategy. For more than four attributes, the deviation-coefficient is obtained by subtracting the sum of the coefficients associated with the high attributes from the sum of the coefficients associated with the low attributes.

The TCD model is similar to the scatter model in that both represent NLNC strategies by a "correction" to the linear model, a correction which depends on deviations among attributes. Indeed, in the two attribute cases, the two models yield exactly the same fit (Czaczkes, Ganzach, & Venezia, in preparation, give an analytical proof. See also Table 2 below). The hyperbolic and parabolic models differ from the scatter and TCD models, but are quite similar to each other, in that both treat judgment as a multiplicative function of attribute values.[5]

One property of the scatter and TCD models that make them potentially more attractive than the hyperbolic and parabolic models is that the results of the former two models are invariant under affine transformation of the raw data. This implies, for example, that adding a constant to the attribute values will not change the regression results. On the other hand, the results of the hyperbolic and parabolic models will be changed under such transformation. In other words, the fit of these latter models are arbitrary in that they depend on the scale used by the experimenter (see also Goldberg, 1971, pp. 470–471).

There are also two issues in comparing the scatter and TCD models that are important to mention. The TCD model has the advantage of representing more accurately conjunctive/disjunctive strategies as described above, which may lead to a better fit to empirical data, if subjects indeed use these strategies. On the other hand, this model also requires the estimation of more parameters than the scatter model, especially when the number of attributes increases. Since the number of degrees of freedom that can be obtained in judgment experiments is limited, this may create large estimation errors.

So far, there have been several studies that examined NLNC judgment strategies using a regression approach (Slovic & Lichtenstein, 1971). Most of these studies relied on Einhorn's models. For example, Einhorn, Komorita, and Rosen (1972) used these models in studying the evaluation of political candidates; Einhorn (1972) used them in the study of medical judgment; Mertz and Doherty (1974) used them to study the evaluation of college success by high-school counselors; Wright (1974) used them to study the effect of time pressure on judgment; Ogilvie and Schmitt (1979) used them to examine situational influences on information utilization; and Billings and Marcus (1983) relied on these models in comparing the process tracing and the policy capturing techniques in the study of decision making behavior.

Due to the wide interest in the study of NLNC judgments strategies (see Wiggins & Hoffman, 1968; Goldberg, 1969, for examples of studies in the regression approach that did not use Einhorn models. See Hoffman, Slovic, & Rorer, 1968; Anderson, 1972; Birnbaum, 1974; and Skowronski & Carlston, 1987 for examples of studies in the ANOVA approach. See Hammond & Summers, 1965; Wallsten & Budescu, 1981; and Meyer, 1987 for examples of studies in other approaches) it seems to be important to examine Einhorn's models against alternative models, thereby enabling researchers to have a "better shot" at detecting NLNC judgments in their data. So far, there were two attempts to compare the power of Einhorn's models to alternative nonlinear models, but both were unsuccessful from the point of view of identifying a better nonlinear model. Goldberg (1971) examined the effectiveness of various nonlinear models, but his results indicate that all these models are inferior to the linear model in modeling MMPI-based clinical judgments. Brannick and Brannick (1989) did succeed in showing that some nonlinear models can give a better fit than the linear model, but failed to show meaningful differences among the power of these nonlinear models, and in particular between the power of the scatter and parabolic models (they did not examine the hyperbolic model).

In this paper we do show that the scatter model, as well as the TCD model, perform better than the hyperbolic and parabolic models in a variety of judgment tasks. Our approach is similar to that of Brannick and Brannick (1989) and Goldberg (1971), in that we apply the competing models to various empirical datasets and examine which model gives a better fit for the data. These datasets were obtained in experiments that were performed to examine theoretical predictions with regard to the particular NLNC strategy used.

[5] Einhorn (1970) uses the concept of utility to analyze judgment. By using this concept, the similarity between the two models is even more apparent. The parabolic model is a logarithmic utility function, while the hyperbolic model is a logarithmic disutility function. To calculate disutility, each attribute value is subtracted from a constant (the constant a_i in the hyperbolic model equation). This transformation creates scales in which the higher the attribute value the higher the disutility. Disutility is a logarithmic function of these new scales. Finally, the result is multiplied by -1 to transform disutility to utility.

Therefore, they also allow the examination of the competing measures for NLNC strategies against these apriori predictions.

HOMOGENEOUS NLNC STRATEGIES

Deviation from linearity may be homogeneous or heterogeneous. In the homogeneous case, NLNC judgments are associated with one type of strategy (e.g. conjunctive strategy). We will call this strategy the *dominant* strategy. In the heterogenous case, they are the result of more than one type of strategy (e.g., they are associated with both disjunctive and conjunctive strategies).

In this section we examine the performance of the alternative models in 10 datasets associated with five judgment experiments. Each experiment consists of one experimental condition and one control condition. In the experimental conditions it was expected that either a conjunctive or a disjunctive strategy would be the dominant strategy. In the control conditions reliance on the dominant strategy was expected to be lower. The 10 datasets are described in the appendix, the theoretical prediction about the type of NLNC strategies to be expected in each of them is given in the second column of Table 1, and the rationale for the prediction is given in the appendix. Procedural details of the experiments, are given in columns 3 through 6 of Table 1 and in the Appendix. For further details of the experimental procedures and the rationale behind the theoretical expectations see Ganzach (1993); Ganzach (1994); Ganzach and Czaczkes (in preparation).

Aggregate Level Measures

Comparison of model fit. In most previous research, NLNC models were examined by evaluating their fit to the data. In this section we follow this tradition, and perform a double cross validation on the judgments of each subject using the linear model and the four alternative models (Cross validation is the recommended method for comparing model fit, especially when models differ in the number of parameters that have to be estimated. See Cohen and Cohen, 1983). The results are expressed in terms of the multiple correlation between the actual judgments and the predicted values of the models. For each dataset, the means and standard deviations of the multiple correlations are presented in columns 7 through 11 of Table 1 (the two cross validation correlations were averaged for each subject).

We compared the different models by performing a paired t test on the multiple correlations (this method is used for comparison between the models throughout the paper). The results of this test indicate that the linear model gives a better fit than both the parabolic and hyperbolic models in all 10 datasets. The effect is particularly strong for the hyperbolic model ($p < .0001$ for all datasets), but is also substantial for the para-

TABLE 1

Summery Results for Datasets Associated with Homogeneous Strategies

Data set	Theoretical prediction	No. of subjects	No. of judgments	No. of attributes	Correlation between attributes	Cross validated correlation: Linear	Scatter	Parabolic	Hyperbolic	TCD	Scatter coefficent	Coefficient deviation	Individual configurality: Percent significant subjects	Percent homogeneity among significant subjects	Percent homogeneity among all subjects
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Conjunctive	24	60	3	.0, −.7	.716	.765	.711	.475	.744	−.637	−.899	70	88	83
						(.131)	(.111)	(.136)	(.207)	(.119)	(.700)	(.989)			
2	Control for 1	24	60	3	.0, −.7	.787	.805	.699	.646	.790	−.131	−.235	38	56	58
						(.113)	(.092)	(.130)	(.116)	(.099)	(.610)	(.859)			
3	Disjunctive	30	42	3	0	.841	.840	.797	.699	.825	.620	.977	17	100	87
						(.122)	(.123)	(.149)	(.091)	(.133)	(.571)	(.855)			
4	Control for 3	25	42	3	0	.852	.842	.786	.676	.825	.361	.613	12	75	72
						(.108)	(.113)	(.162)	(.098)	(.130)	(.577)	(.897)			
5	Conjunctive	24	42	3	0	.860	.863	.817	.677	.827	−.409	−.590	25	100	71
						(.065)	(.059)	(.082)	(.087)	(.087)	(.815)	(1.215)			
6	Control for 5	25	42	3	0	.876	.873	.832	.695	.860	.045	.102	12	67	60
						(.075)	(.079)	(.094)	(.115)	(.079)	(.695)	(1.040)			
7	Conjunctive	29	120	10	.2, .3, .4	.671	.668	.667	.632	.622	−.084	−.287	20	100	86
						(.070)	(.070)	(.080)	(.067)	(.093)	(.091)	(.264)			
8	Control for 7	29	120	10	.2, .3, .4	.659	.658	.640	.573	.615	.052	.211	17	100	59
						(.121)	(.099)	(.128)	(.109)	(.109)	(.145)	(.359)			
9	Disjunctive	30	120	10	.2, .3, .4	.687	.701	.639	.607	.668	.298	.615	57	100	93
						(.086)	(.083)	(.089)	(.093)	(.097)	(.184)	(.453)			
10	Control for 9	30	120	10	.2, .3, .4	.641	.641	.605	.605	.602	.099	.077	23	100	87
						(.097)	(.107)	(.103)	(.092)	(.122)	(.115)	(.337)			

Note. Numbers in parentheses are standard deviations.

bolic model (ns, $p < .0001$, $p < .0001$, $p < .0008$, $p < .001$, $p < .0001$, ns, $p < .0007$, $p < .0001$, $p < .0001$ for datasets 1 through 10, respectively). The fit of the linear model is also higher than the fit of the TCD model ($p < .05$, ns, $p < .01$, $p < .001$, $p < .0001$, $p < .006$, $p < .005$, $p < .03$, $p < .005$, $p < .0001$ for datasets 1 through 10, respectively).

On the other hand, the scatter model fares much better. In two of the five datasets in which there is an a priori expectation for NLNC judgment strategies—datasets 1 and 9—the cross-validated multiple correlation of the scatter model was significantly higher than that of the linear model ($p < .004$, $p < .01$, respectively), while in the other datasets the differences between these two models were quite small. Note also that the fit of the scatter model is substantially higher than the fit of the parabolic model ($p < .001$, $p < .0001$, $p < .0001$, $p < .0001$, $p < .0002$, $p < .0001$, ns, $p < .04$, $p < .0001$, $p < .0001$ for datasets 1 to 10, respectively), the hyperbolic model ($p < .0001$ for all 10 datasets), and the TCD model ($p < .0005$, $p < .003$, $p < .007$, $p < .1$, $p < .0002$, $p < .03$, $p < .0001$, $p < .0001$, $p < .0001$, $p < .0001$ for datasets 1 to 10, respectively). Thus, no matter what strategy is used by the subjects, the scatter model provides better fit than any of the alternative nonlinear models.[6]

The nonlinear coefficients. Column 12 of Table 1 presents the average of the scatter coefficient for each dataset, while column 13 presents the average deviation-coefficient. It is clear from these results that the best indicators for NLNC judgment strategies are those derived from the nonlinear coefficients. The mean scatter coefficient was significantly different from zero for all five datasets in which a theoretical prediction about NLNC judgment strategies existed ($p < .0002$, $p < .0001$, $p < .02$, $p < .0001$, and $p < .0001$ for datasets 1, 3, 5, 7, and 9, respectively. The signs are in line with the theoretical predictions). The scatter coefficient also revealed NLNC judgment strategies for three of the five control datasets for which no strong theoretical prediction about NLNC judgment strategies was available ($p < .005$, $p < .06$, $p < .0001$ for datasets 4, 8, and 10, respectively). Similarly, the deviation-coefficient was significantly different from zero for the five former datasets ($p < .0001$, $p < .0001$, $p < .02$, $p < .0001$, $p < .0001$ for datasets 1, 3, 5, 7, and 9, respectively) and for three of the five latter datasets ($p < .004$, $p < .01$, $p < .02$ for datasets 4, 8, and 10, respectively) (note that a positive value of the deviation-coefficient indicates a disjunctive strategy, while a negative value indicates a conjunctive strategy).

Using the nonlinear coefficients as a measure for NLNC judgment strategies allows for the representation of judgment of each task as located on a conjunctive–disjunctive continuum, where the location of judgment on this continuum is expressed by the average value of the nonlinear coefficient. To illustrate this view, consider how the scatter coefficient can be used to estimate not only the type of deviation from linearity in a certain task (i.e. not only whether judgments are disjunctive or conjunctive) but also the degree of this deviation (i.e. how "much" disjunctive or conjunctive they are). One example emerges from comparing dataset 9 and its control dataset, dataset 10. Although judgment in both datasets is highly disjunctive (in both the scatter coefficient is significantly positive), a comparison between the average scatter coefficients indicates that they were more disjunctive in dataset 9 than in dataset 10 (the average scatter coefficient in dataset 9 is more positive than the average scatter coefficient in dataset 10, $p < .0001$ using a paired t test).

Individual Level Measures

The previous section was concerned with detecting NLNC strategies on the aggregate level, i.e. the measures examined were group averages. However, there are occasions in which one may be interested in detecting NLNC strategies on the individual level. One reason why the scatter model is very convenient for this purpose, is that it allows testing for the null hypothesis of linearity on the individual level, by examining whether the additional variance added by the scatter term differs from zero.

The scatter model also allows for examining the degree to which individual strategies deviate from linearity. The more negative [positive] the scatter coefficient the more conjunctive [disjunctive] the strategy. In other words, individual strategies can be viewed as located on a conjunctive-disjunctive continuum ranging from a highly negative to a highly positive scatter coefficient, where zero represents linear strategy (note, however, that on the aggregate level, zero average scatter coefficient may or may not represent linear strategy. This issue will be further discussed below).

The detection of NLNC strategies on the individual level is relevant to questions concerning homogeneity in judgment strategies. One question is whether an observed aggregate conjunctivity or disjunctivity (as measured, for example, by the average scatter coefficient) is associated with homogeneity in reliance on NLNC strategies, i.e., whether it reflects a general tendency for such strategy in the population. The last col-

[6] We also performed additional analyses in which the fit of the "two stage" version of the scatter model (Footnote 2) was examined. We found the fit of the simpler version of the model to be somewhat higher. One reason for that may be that the two stage version may require the estimation of additional parameters, and thus lead to larger estimation errors.

umns of Table 1 present data relevant to this question. Column 14 presents the proportion (in percent) of subjects whose scatter coefficient is significantly different from zero, column 15 presents the proportion of subjects whose strategy is the dominant strategy out of the "significant" subjects, and column 16 presents the proportion of subjects whose strategy is the dominant strategy out of all subjects. For example, for dataset 1, the dominant strategy is conjunctive, 83% of the subjects had a negative scatter coefficient, 70% of the subjects had a significant scatter coefficient, and out of this 70%, 88% had negative coefficient.

These last columns of Table 1 indicate that in our datasets, observed aggregate conjunctivity or disjunctivity is associated with homogeneity in NLNC strategies and not with few highly conjunctive or disjunctive subjects. For example, these columns indicate that there is high homogeneity in the datasets in which the scatter coefficient is significantly different from zero (datasets 1, 3, 4, 5, 7, 8, 9, 10).

Finally, it should be emphasized that the hyperbolic and parabolic models cannot be used for detecting deviations from linearity on the individual level. These models do not offer a significance test for conjunctivity or disjunctivity of individual subjects, since the total variance explained by these models cannot be partitioned to linear and nonlinear variance.

HETEROGENEOUS NLNC STRATEGIES

In this section we present original experimental data associated with heterogeneous NLNC judgment strategies. In this case, aggregating over the cross-validated correlations of the scatter and TCD models is still appropriate, but aggregating over the average nonlinear coefficients and the average cross-validated correlation of the parabolic and hyperbolic models is inappropriate. To illustrate this, consider a case in which half of the subjects are disjunctive and half are conjunctive. In this case, the average scatter coefficient is close to zero, and therefore does not reflect reliance on NLNC strategies. On the other hand, the average cross validated correlation of the scatter and TCD models are still good indicators of such strategies, since for these measures, conjunctive and disjunctive strategies do not "cancel" each other. Note, however, that the averages of these measures only indicate reliance on NLNC strategies in general, but do not indicate what type of NLNC strategy is used. As for the average cross validated multiple correlation of the parabolic [hyperbolic] model, it is likely to be an even poorer indicator for NLNC strategies than in the homogeneous case (in which it was found to be a very poor indicator), since it provides especially low fit for the subjects whose strategy is disjunctive [conjunctive].

Procedure

First year business students judged the "chances of academic success" of 44 hypothetical classmates based on their intelligence and motivation scores. Both scores were uniformly distributed, and the ranges were 100 to 140 for intelligence (presented as an IQ scale) and 1 to 100 on motivation (presented as a percentile scale). Judgment was given on a 1 to 9 likert type scale.[7]

There were two conditions in the experiment. In one ($n = 19$), the inter-attribute correlation was $-.7$. In the other ($n = 19$) it was zero. The reason for choosing the negative correlation condition is that the lower the inter-attribute correlation, the more sensitive is model performance to misspecification errors—to differences between the true strategy and the model (Einhorn, Kleinmuntz, & Kleinmuntz, 1979). In other words, the chances of detecting differences between nonlinear models and the linear model if the "true" strategy is indeed nonlinear are higher in negative inter-attribute correlation conditions (see Einhorn, 1970; Goldberg, 1971, Newman, 1977. A detailed review of this issue is given by Johnson Meyer and Ghose, 1989, pp. 255–256).

Results

Judgments in this experiment are heterogeneous in regard to reliance on NLNC strategies (although there is some tendency towards conjunctivity). In particular, in the negative correlation condition, eight of the scatter coefficients were positive, two of them significantly so ($p < .05$, $P < .05$, for the null hypothesis the scatter coefficient equals zero), while 11 were negative, six of them significantly ($p < .0001$, $p < .001$, $p < .003$, $p < .01$, $p < .02$, $p < .03$). In the zero correlation condition, 10 of the coefficients were positive, two of them significantly so ($p < .003$, $p < .06$), while nine were negative, three of them significantly ($p < .0004$, $p < .008$, $p < .0005$).[8] (The results of the deviation-coefficient are not discussed since they are identical to the results of the scatter coefficient).

It is clear from these results that in both conditions many subjects relied on NLNC strategies. However, aggregating over this measure would not reveal reli-

[7] There are two possible theoretical predictions about the configurality that this task may elicit. One is that in judging peers, people will tend to give the benefit of the doubt, and therefore to be disjunctive (Ganzach, 1993). The other is that in judging success on the basis of motivation and ability people will use a conjunctive type (multiplicative) rule (Anderson and Butzin, 1974).

[8] In presenting the results of significance tests on the individual level we followed Brannick and Brannick (1989). Note, however, that the p values may overestimated, because errors of the model may be correlated within individuals.

TABLE 2
Cross-Validated Correlations for Datasets Associated with Heterogeneous Strategies

Model	Cross-validated correlation	
	Negative correlation	Zero correlation
Linear	.674	.833
	(.298)	(.180)
Scatter	.703	.828
	(.249)	(.193)
TCD	.703	.828
	(.249)	(.193)
Parabolic	.658	.828
	(.319)	(.192)
Hyperbolic	.632	.827
	(.265)	(.158)

Note. Numbers in parentheses are standard deviations.

ance on such strategies. In both conditions, the average scatter coefficients did not differ significantly from zero in either condition ($p > .6$, $p > .2$ for the zero and negative correlation condition, respectively).

To examine model's fit we performed double cross validation on the judgments of each subject using the linear model and the three alternative models. The results of these cross validations are given in Table 2. It is clear from the table that in the negative correlation condition, the scatter and TCD models give the best fit to the data (and that they give the same fit). In particular, a comparison between the fit of these models and the fit of the linear model indicates the existence of NLNC strategies ($p < .03$), while a comparison between the parabolic model and the linear model does not ($p > .3$). The fit of the hyperbolic model is much lower than the fit of the other two models.

In the orthogonal condition there were no significant differences between the linear, parabolic and scatter (TCD) models. The hyperbolic model was significantly lower than the linear, scatter and parabolic models ($p < .005$, $p < .0005$, and $p < .05$, respectively).

CONCLUDING REMARKS

The central purpose of this paper is to examine alternative models to the parabolic and hyperbolic models. The results presented demonstrate that in a variety of judgment tasks the scatter and TCD models are more effective in detecting NLNC strategies than the hyperbolic and parabolic models. The scatter model is particularly effective. In all of the datasets examined, the cross validated multiple correlation of this model was higher than the cross validated multiple correlation of the parabolic and hyperbolic models. The scatter model detected NLNC strategies in 3 of the 12 datasets using cross validated multiple correlation as a measure for NLNC strategies, and in 8 of these datasets using the scatter coefficient as a measure for NLNC strategies. Furthermore, in these 8 latter datasets the sign of the average scatter coefficient was in line with theoretical predictions about reliance on NLNC strategies. In contrast, the hyperbolic and parabolic models did not detect NLNC strategies in any of the datasets.

The failure of the parabolic and hyperbolic models against a "blue print" (the measures for NLNC strategies derived from the scatter model) suggests that past results indicating that nonlinear models are generally inferior to linear models in modeling judgment (e.g., Goldberg, 1971; Ogilvie & Schmitt, 1979) are questionable. They may simply result from using weak NLNC models. The hyperbolic model appears to be especially weak. The scatter model outperforms it even more than it outperforms the parabolic model (see Table 1). Thus, the complete failure of previous research in documenting disjunctive strategies (against a limited success in documenting conjunctive strategies) may be partially due to the fact that the hyperbolic model is especially weak.[9]

While the scatter model's superior ability to detect NLNC strategies in judgment is its most important advantage over competing models, it has other advantages arising from the possibility of using the scatter coefficient—and not only model fit—as a measure for NLNC strategies. On the individual level, this measure allows for the representation of individual judgment strategies as located on a continuum ranging from conjunctive to disjunctive, where zero represents a linear strategy; it also allows for the examination of the reliability of deviation from linearity on the individual level by testing the deviation of the scatter coefficient from zero.

On the aggregate level, the average scatter coefficient is a more powerful measure than any model fit based measures when judgments are homogeneous. When judgment are heterogenous, the interpretation of the average scatter coefficient is more problematic (e.g., a zero average coefficient may result either from linearity or heterogeneity in NLNC strategies). However, even in this case the average scatter coefficient is useful in examining hypotheses about the typical judgment strategy in the population, and in particular hypotheses concerning the impact of various conditions on this strategy (e.g., hypotheses about the influence of the complexity of the judgment or the level of involvement on judgment strategies. See Ogilvie & Schmitt, 1979; Einhorn, 1971; Ganzach, 1993).

[9] This particular weakness of the hyperbolic model is likely to be due to the arbitrary constants a_is used in the model. Indeed in all the datasets of Table 1, even those in which judgment was found to be disjunctive by the scatter model, the hyperbolic model does worse than all other models, including the parabolic model.

APPENDIX

Experiment 1

Dataset 1 (experimental condition). Judgment of cars based on (1) engine volume, (2) model, and (3) economics. The attributes were presented in the form of bar graphs. Judgments are expected to be conjunctive because of the tendency to emphasize negative aspects of the information in judging high involvement products (Mowen, 1990). This tendency is especially strong because of the visual saliency effect (Jarvenpaa, 1990)—extreme attributes are very salient in visual presentation of attributes' information (Ganzach and Czaczkes, in preparation).

Dataset 2 (control condition). Judgment of cars based on the same attributes as above. The attributes were presented in the form of numbers. Judgments are expected to be somewhat conjunctive because the judged object is a high involvement product, but not as conjunctive as judgments in dataset 1 because extreme attributes are not as salient as in numerical representation (Ganzach and Czaczkes, in preparation).

Experiment 2

Dataset 3 (experimental condition). Judgment of university professors based on their success in (1) capturing students' interest, (2) achieving appropriate students' participation, and (3) teaching analytical tools. Judgments are expected to be disjunctive because in judging human objects people tend to be lenient and therefore emphasize the more positive attributes (Ganzach, 1993).

Dataset 4 (control condition). Judgment of university courses based on the same attributes as above. Judgments are not expected to be as disjunctive as in dataset 3, because there is not a strong leniency effect in judgment of non-human objects (Ganzach, 1993).

Experiment 3

Dataset 5 (experimental condition). Judgment (by student subjects) of fellow students as potential partners for home assignments, the grades of which weigh heavily in an important course. The attributes on which the judgments were based are (1) the intellectual ability of the student, (2) his/her willingness to share in the work, and (3) his/her likability. Judgments are expected to be conjunctive because the increased strictness associated with high stake judgments lead judges to put an emphasis on negative attributes (Ganzach, 1993).

Dataset 6 (experimental condition). Judgment by student subjects playing the role of teaching assistants requested by the professor to evaluate students as partners for preparing home assignments. The attributes were the same as in dataset 5. Judgments are not expected to be as conjunctive as in dataset 5 because the stake in these judgments is low (Ganzach, 1993).

Experiment 4

Dataset 7 (experimental condition). Social workers' intervention judgment of children from unfavorable home environment based on ten attributes describing the environment. Judgments are expected to be conjunctive because social workers' theories suggest that even a few favorable home characteristics (e.g., favorable mother's attitude), should lead to a recommendation of a minimal intervention program (i.e., heavier weight is assigned to attributes that lead to low judgment) (Ganzach, 1994).

Dataset 8 (control condition). Experts' risk judgment of children from unfavorable home environment based on the same 10 attributes. Judgments are expected to be less conjunctive because social workers' theories about risk do not emphasize favorable home characteristics (Ganzach, 1994).

Experiment 5

Dataset 9 (experimental condition). Laymen's risk judgment of children from unfavorable home environments based on the same 10 attributes. Judgments are expected to be disjunctive because layman theories suggest that even a few unfavorable home characteristics (e.g., unfavorable mother's attitude) lead to high risk for the child (Ganzach, 1994).

Dataset 10 (control condition). Laymen's intervention judgment of children from unfavorable home environments based on the same 10 attributes. Judgments are expected to be less disjunctive than judgment in dataset 9, because laymen theories of intervention are not as disjunctive as their theories of risk (Ganzach, 1994).

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