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Analyzing the Use of Information in Investment Decision Making: A Methodological Proposal

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I. Introduction

Foresightful investment analysts have long recognized the need to understand more clearly the detailed processes underlying investment decisions -- especially decisions made by acknowledged experts. For example, Bernhard observes that, if the mental process of consistently successful investors are intuitional, that intuitional reasoning must be made understandable.[1] In a similar vein, others have argued that by compelling the investment analyst to translate his vague attitudes, opinions, and reasons into explicit quantities, the analyst's thoughts are brought out into the open where they can be observed, evaluated, and tested.[2]

Researchers in the areas of economics, finance, and psychology have recently taken up the challenge of simulating and describing the judgment process. There are, at present, a number of methods that should be of interest to persons concerned with the dynamics of investment decisions. The objective of this paper is to provide a brief introduction to this work and to present an experiment that illustrates the use of one such method for quantitatively describing the use of information in investment decisions. Due to limitations of the sample of subjects and the particular cases being judged, the reader should view the experiment as a methodological illustration -- not a finished empirical investigation.

II. Overview of Previous Research and Methods

A. Complex Simulation

One of the most impressive attempts to describe complex decision making has been carried out by Clarkson, who undertook to simulate the portfolio selection processes of a bank's trust investment officer.[3] Clarkson collected a large number of protocols based on the verbalized reflections of the investment officer who was asked to "think aloud" while reviewing past and present decisions. Using these protocols as a guide, the investment process was translated into a sequentially branching computer program. When the validity of the model was tested by comparing its selections with actual portfolios selected by the trust officer, the correspondence between actual and simulated portfolios was found to be remarkably high.[4]

B. Linear Models

Clarkson's work shows that, given patient and intelligent effort, many of the expert's cognitions can be distilled into a form capable of being simulated by a computer. However, this paper will emphasize yet another approach -- one that attempts to provide less of a sequential analysis and more of a quantified, descriptive summary of the way that a decision maker weights and combines information from diverse sources. This approach aims to develop a mathematical model of the decision maker and requires less time and effort on the part of investigator, subject, and computer. It forms a nice compromise between the complex "computer model" of Clarkson's and the relatively naive approaches of the pre-computer era -- such as simply asking the decision maker how he makes his judgments. The philosophy and techniques for developing such mathematical models are discussed in considerable detail by psychologists Hoffman, Hammond, and Goldberg.[5]

The basic approach requires the decision maker to make quantitive evaluations of a fairly large number of cases, each of which is defined by a number of quantified cue dimensions or characteristics. A financial analyst, for example, could be asked to predict the long-term price appreciation for each of 50 securities, the securities being defined in terms of cue-factors such as their P/E ratios, corporate earnings growth trend, dividend yield, etc. Just as investigators interested in modeling the characteristics of the market have suggested using multiple correlational procedures to capture the way in which the market weights and responds to these factors, Hoffman, Hammond, and others would suggest fitting a regression equation to the analyst's judgments to capture his personal weighting policy. The resultant equation would be:

$$\hat{J}_{pa} = b_1X_1 + b_2X_2 + \ldots b_kX_k \qquad (1)$$

where $\hat{J}_{pa}$ = predicted judgment of price appreciation; X_1, X_2 ... X_k are the quantitative values of the defining cue factors (i.e., P/E Ratios, earnings, etc.); and b_1, b_2 ... b_k are the weights given to the various factors in order to maximize the multiple correlation between the predicted judgments and the actual judgments. These weights are assumed to reflect the relative importance of the factors for the analyst. Equation 1 is known as the linear model.

Psychologists have found linear models to be remarkably successful in their ability to predict judgments of such diverse criteria as psychiatric diagnosis, malignancy of ulcers, job performance, and the riskiness and attractiveness of gambles.[6] Political scientists have found linear models useful for describing judicial decision processes in workmen's compensation and civil liberties court cases.[7] Researchers interested in simulating financial and managerial decisions have independently discovered the value of linear models. For example, Bowman and Kunreuther successfully fit linear models to decisions concerned with production scheduling and Hester used regression analysis to develop a "loan offer function" representative of the lending policy of a particular bank.[8]

C. Configural Models

When an analyst associates good investment decisions with complex and interrelated decision rules, chances are that he envisages types of patterned or configural relationships rather than the linear combination rule discussed above. Configurality means that the analyst's interpretation of an item of information varies depending upon the nature of other available information. An example of configural reasoning involving price changes, volume, and market cycle is given by Loeb:

> "Outstanding strength or weakness can have precisely opposite meanings at different times in the market cycle. For example, consistent strength and volume in a particular issue, occuring after a long general decline, will usually turn out to be an extremely bullish indication. . . . On the other hand, after an extensive advance which finally spreads to issues neglected all through the bull market, belated individual strength and activity not only are likely to be shortlived but may actually suggest the end of the general recovery. . . ."[9]

Such introspective reports indicate that analysts believe that factors relevant to investment decisions should often be interpreted configurally. Therefore, it is important that techniques used to describe judgment be sensitive to such processes. The linear model can be made sensitive to configural effects by incorporating cross-product terms into the policy equation of the judge. When models become this complex, however, the proliferation of terms in the equations becomes so great that proper estimation of the weights for the configural and nonconfigural terms can be difficult. For this reason some investigators have turned to a related model, that of the analysis of variance (ANOVA), to describe complex judgment processes.

III. The ANOVA Model[10]

The structural model underlying ANOVA is quite similar to that of multiple regression. However, the ANOVA model typically imposes two important restrictions on the factors that describe the cases being judged: (a) the levels of the factors must be categorical (e.g., good vs. average vs. poor, up vs. down, etc.) rather than continuous variables;[11] and (b) the factors must be orthogonal (uncorrelated); in other words, if P/E ratio and dividend yield are two factors, they should be uncorrelated across the set of stocks. In return for these restrictions, the ANOVA model efficiently sorts the information about linear and configural judgment processes into nonoverlapping and meaningful portions.

For illustrative purposes, consider the situation in which an analyst is asked to judge the potential price appreciation of several securities on the basis of just two factors, support trend of prices and market volume trend, each of which could be either up (+) or down (-) for a given stock. Imagine also that the judgments are made on a rating scale varying from 1 (very little potential) to 9 (very great potential). The ANOVA model, applied to this situation, would assert that:

$$J_{ijk} = M + \alpha_j + \beta_k + \gamma_{jk} + e_{ijk} \quad ,$$

where:

J_{ijk} is the analyst's rating of the i^{th} stock, a stock that was observed to be in condition (level) j with respect to support trend and condition k with respect to volume trend;

M is the mean of the ratings over all the stocks, regardless of their level of support and volume;

α_j is the main effect of support trend;

β_k is the main effect of volume trend;

γ_{jk} is the interaction effect created by combining support and volume over and above any effects associated with these factors considered separately; and

e_{ijk} is a random error component.

The main effects, α_j and β_k, are defined as follows:

$$\alpha_j = M_j - M$$

$$\beta_k = M_k - M$$

where M_j and M_k are the mean ratings of all stocks having level j with respect to support trend and level k with respect to volume trend, respectively. Finally, γ_{jk}, the interaction effect, is defined as:

$$\gamma_{jk} = M_{jk} - M - \alpha_j - \beta_k = M_{jk} - M_j - M_k + M$$

where M_{jk} is the mean rating for all stocks jointly having level j of support and level k of volume.

To further illustrate the meaning of main effects and interactions and their relationship to the interpretation and use of information, consider the following example. Suppose that the mean rating given to a number of stocks varies with support and volume as indicated in Table 1. Here we see that the ratings vary systematically with changes in support ($\alpha_j \neq 0$) but are not influenced by changes in volume ($\beta_k = 0$). This systematic variation with support is called the main effect of support.[12] When a factor has a statistically significant main effect, we shall assert that the analyst was relying on that factor when making his ratings. The greater the differences between the mean ratings at each of the levels of a factor and the overall mean, M, the greater the influence of that factor upon the judgments.

Insert Table 1 about here

Sometimes two or more factors might each produce significant main effects. An example is shown in Table 2. Here the mean judgment for each of the four cells equals an additive combination of the effects of the individual factors.

That is, stocks that are characterized by a favorable level for both factors receive a higher mean rating than do stocks for which only one factor is favorable. When factors have an additive effect, a change in one factor has the same effect on the judgments regardless of whether the other factor is present or absent -- i.e., the effects of the factors are independent of one another. The relative size of the effects indicates the relative importance of the factors. In this example, a change in volume produced twice the effect of a change in support.

Insert Table 2 about here

In contrast to a simple additive combination of factors is an <u>interactive</u> combination, in which the effect of a particular factor is contingent upon the levels of some one or more other factors. Interactions embody the essence of what we have been calling patterned or configural judgments. An example of an interactive combination of support and volume is shown in Table 3. In the example, the main effects due to each factor are the same as those in Table 2. However, these main effects no longer adequately characterize the separate influence of the factors. The meaning of support trend is dependent upon whether volume trend is up or down. Alternatively, the interpretation that the analyst gives to volume is dependent on the level of support.[13]

Insert Table 3 about here

Configurality generally represents a relatively complex type of information use -- but not always. Einhorn noted that some very simple cognitive processes are configural in nature.[14] Among these are disjunctive rules, whereby the judgment depends upon the single most outstanding cue-factor and conjunctive rules whereby the object being judged has to meet a certain minimum standard on all factors before it can receive a high evaluation.

Although the introspections of experts concerning the manner in which they make judgments are replete with statements about their dependence upon patterns or configurations, there have been few attempts to demonstrate such complex processes empirically. The ANOVA technique is important because, by isolating the effects of interactions from those of main effects, it makes the empirical description of configural judgments feasible.

IV. An Experiment Illustrating the ANOVA Technique

A. Subjects

The subjects were 13 stock brokers and 5 students. The students were working towards an MBA and were about to complete a graduate course in investment analysis. Nine of the brokers came from three brokerage firms located on the west coast. The remaining four brokers came from one firm located in Chicago. On the average, the brokers had about 4 1/2 years of experience. Their median length of experience was 2 years and the range was 6 months to 15 years.

B. Procedure

To apply ANOVA to the study of investment decisions, one first selects a set of presumably relevant factors (i.e., items of information or dimensions along which a stock can be described) and then constructs hypothetical stocks such that specific combinations of these factors are represented. Judgments are made by the subjects about each of these stocks, and these are analyzed by means of an ANOVA model. Main effects and interactions are calculated and tested for statistical significance.

In the present study common stocks were described by means of eight factors commonly provided in Standard & Poor's Standard Listed Stock Reports. Each factor could take one of two levels. The factors, with their abbreviations and levels in parentheses, were:

(a) Industry (IND -- Stable vs. Dynamic)

(b) Resistance Level (RES -- Up vs. Down)

(c) Support Level (SUPP -- Up vs. Down)

(d) Volume Trend (VOL -- Up vs. Down)

(e) Near Term Prospects (NTP -- Good vs. Poor)

(f) Profit Margin Trend (PMT -- Up vs. Down)

(g) Price/Earnings Ratio Comparison (PER -- Good vs. Poor)

(h) Earnings per Share Yearly Trend (EYT -- Up vs. Down)

Next, hypothetical stocks were constructed by combining levels of these eight dichotomous factors so that pairs of factors were uncorrelated across the total set. This property is desirable if the independent influence of each factor is to be estimated with minimal ambiguity. One way to insure such independence would have been to construct all combinations of factors (2^8 or 256 stocks in this case). Doing so would have permitted an analysis of all main effects and interactions among any combination of the eight factors. However, for purposes of saving time and effort on the part of the subjects, a smaller number of companies was employed. If one is willing to forego the ability to study higher-order interactions (i.e., interactions involving a large number of variables) and to assume that their influence would be negligible, it is possible, by means of a fractional replication design, to evaluate the main effects and lower-order interactions with a considerably reduced number of stimuli. For the present study, a 1/4 fractional replication of a 2^8 factorial ANOVA design was used to guide the manner in which the hypothetical companies were constructed.[15] This produced a set of 64 stocks. This reduction of stimulus companies from 256 to 64 resulted in the confounding of main effects and two-way interactions with certain of the higher-order interactions. Other higher-order interactions served to estimate the error term in the ANOVA. Thus, if configural use of three or more factors did occur, the error term would have been inflated.

Figure 1 illustrates the way in which information about a company was displayed to the subjects. The 64 stocks were preceeded by eight practice stocks and were bound in a notebook. The subjects worked on the judgments in their leisure time. They were not told that the companies were hypothetical. They reported that the task was extremely interesting and several noted that they were able to conjure up images of companies as they read the information about the stocks. The average amount of time spent in evaluating the companies was 2 1/2 hours. The range was between 1 and 5 hours. The testing was done during the months of March and April of 1969.

Insert Figure 1 about here

The subjects were instructed as follows:

> "Your task as an account executive is to evaluate each firm with regard to its potential capital appreciation, with a time horizon of six to eighteen months. Your judgment will be on a scale from 1 to 9, with 1 representing an expectation of a substantial decrease in the value of the stock, 5 meaning you expect no significant change, and 9 being an expectation of a substantial increase in value. You are free to use these numbers and the numbers in between them in any way that you wish to express gradations in your expectation about a stock.
>
> "Each company's stock should be judged with regard to its possible inclusion into a customer's portfolio. As you make each judgment, keep in mind that the client is a middle-aged businessman, 40 to 45 years old, whose current portfolio is valued at $10,000. During the period of time when the information about the companies was compiled, the stock market was expected to move up very gradually, with no wide fluctuations in either direction.

"There is a set of 8 'practice' companies to familiarize you with the factors and rating scale. It is not expected that you will complete your evaluations in one sitting, and it may be helpful to review your judgment levels on the 'practice' companies before each sitting, to ensure consistent evaluations for the total group of companies.

"It is important that you maintain a consistent frame of reference and 'style of judgment' throughout the study. Therefore, please don't discuss the study or the way you are making your judgments with anyone else until after you have finished."

C. Results

How did the subjects evaluate stocks on the basis of the eight factors? Upon completing his ratings, one broker gave this description of his approach.

"I looked first at Industry to determine the possible range of price swing and then used Near Term Prospects along with P/E Ratio Comparison to determine the play the P/E would have in price action. After a decision was made here, I combined Profit Margin Trend and Earnings per Share Trend to get a feeling for the impact earnings direction would have on price. Then I would combine judgments of P/E Ratio and Earnings per Share to decide the fundamental condition of the company, and I applied my judgment of the company's fundamental condition to the three technical factors. I would then arrive at a decision regarding price movement."

This rather vague verbal description is typical of the way that expertise is usually communicated. It would be difficult for another broker, a student, or an investor to gain much insight into this broker's use of information on the basis of such a report. It is because of the inadequacies of such reports that more precise, quantitative descriptions are valuable.

To illustrate the sorts of analyses that can be performed on these data we shall consider, in detail, the judgments of Brokers 2 and 10. There was rather poor agreement between these two brokers' ratings of the same stock. The correlation between their judgments, across the 64 cases, was only .26. Our analyses will attempt to make the sources of this disagreement explicit.

In order to measure the influence of the various factors, an ANOVA was performed on each broker's responses. Sums of squares and mean squares were computed for each of the eight main effects (individual factors), each of the two-way interactions, and certain three-way interactions that could be estimated with this particular factorial combination of stocks. In addition, two indices of the importance of a factor or interaction were computed for each effect. One was simply the standard calculation of the magnitude of an effect, based upon the degree to which the mean judgment shifted as the levels of a factor varied. The second index, called ω^2, is a function of the squared magnitudes of effect and provides an estimate of the proportion of the total variance in a subject's judgments that could be attributed to a particular main effect or interaction.[16]

Insert Tables 4 and 5 about here

Tables 4 and 5 present the results of the analyses for the two brokers. The ratings of Broker 2 changed significantly with variation in the levels of each of three factors. The most influential factor was Earnings Yearly Trend with Support Level a close second and Resistance Level third. No interactions were significant. Summing the ω^2 indexes for these statistically significant effects, it appears that about 50% of the variance in this broker's responses could be accounted for on the basis of these three main effects. In this analysis, there is no way to determine whether the remaining variance is due to unreliability (error) in the judgments or to higher-order interactions.

Broker 10 exhibited six significant main effects, the strongest of which were due to changes in Near Term Prospects, Earnings Yearly Trend, Profit Margin Trend, and Price/Earnings Ratio. In addition, seven interactions were significant. Thus, Broker 10 was influenced by more (and different) factors than was Broker 2, and interpreted them in more configural ways. A polynomial equation appropriately weighting single factors (main effects) and cross-product terms (interactions) would account for 83% of the variance in the ratings of this broker.[17]

Even though Broker 10, with seven significant interactions, was processing information in a highly configural manner, most of the systematic variance in his judgments could be accounted for (predicted) by means of an additive combination of main effects. The configural processes of the other seventeen subjects accounted for even less variance. On the average, main effects accounted for about 75% of the variance in each subject's ratings while interactions contributed only 4%. The negligible contribution of interactions is a typical finding in other types of judgmental studies and testifies to the remarkable ability of main effects to predict judgments generated by configural processes. Thus fairly simple models can often do an excellent job of simulating configural thought processes.[18]

The finding of a significant main effect or interaction is only a first step in understanding how a judge uses information. It should be followed by an examination of the relevant mean ratings, graphical representation of the effects, and interrogation of the judge concerning the rationale behind his behavior in order to further understand the effect. To illustrate, the significant interaction between the effects of Industry and Near Term Prospects for Broker 10 is pictured graphically in Figure 2. The figure shows that a dynamic industry increases this broker's estimate of a stock's potential when the company's near term prospects are good but decreases its attractiveness slightly when prospects are poor.

Insert Figure 2 about here

An index of the overall importance of a given factor was calculated by summing the magnitude of the main effect of that factor with the magnitudes of all significant interaction effects containing that factor. The summed effect of a given factor was divided by the sum of the effects of all factors. This index of importance was thus a percentage score where the sum of all percentages totaled 100. Table 6 illustrates the calculation of this index for Broker 10.

Insert Table 6 about here

This index was used to compare all 13 brokers and 5 students with one another. The results, presented in the upper half of Table 7, indicated that: (a) there were substantial individual differences in the use of the various factors; (b) both brokers and students relied most heavily on Earnings Yearly Trend; however, the students focused on this variable to a greater extent than did the brokers; (c) brokers exhibited more disagreement with one another than did students; (d) technical indicators (Resistance, Support, and Volume) and Near Term Prospects were used more by brokers than by students; the latter relied more heavily on Earnings Yearly Trend, Price/Earnings Ratio, and Profit Margin Trend.

Insert Table 7 about here

The greater agreement among students and their tendency to rely less on technical market indicators is undoubtedly due to the fact that they were just completing the same course from the same instructor on the topic of security analysis. In contrast, the brokers had more varied kinds of training and experience.

How closely would the judges' subjective impressions of the relative importance of the eight factors conform to the index of importance calculated from the ANOVA model? To answer this question, each subject was asked, after completing his ratings, to distribute 100 points over the eight factors proportionally to his feelings about their importance in determining his judgments. These distributions are presented in the lower half of Table 7. They indicate that: (*a*) subjective weightings were even more variable, across individuals, than were the computed effects; each factor was seen as most important by at least one judge; (*b*) the brokers' subjective weights did not relate closely to their calculated effects (the correlation between subjective and computed effects, across brokers, was only .34);[19] although *Earnings Yearly Trend* had the highest mean subjective and computed weights, the subjective importance attributed to *Industry* was consistently overestimated; also, *Volume* was perceived as more important than *Resistance* and *Support*, a fact that was not confirmed by the calculated effects; (*c*) students' subjective weights were considerably more accurate (their correlation with computed effects was .79), but they, too, overestimated the effects of *Industry* and *Volume*.

The finding that students' subjective weights were more similar to their computed effects than were the subjective impressions of the brokers prompted an examination of the relationship between number of years experience as a broker and accuracy of self-insight. Insight was measured by correlating a broker's subjective weights with his calculated effects across the eight factors. It was hypothesized that, since students were most insightful, the brokers' insight might decrease with increasing experience. Across the 13 brokers, the Spearman rank correlation between the insight index and experience was -.43, which is in the direction specified by the hypothesis.

Why should greater experience lead to less valid self-insight? Perhaps the recent classroom and examination experiences of the students and young brokers necessitated an explicit awareness of the mechanics of the skill that they were attempting to learn. With increasing experience, skilled behaviors become more automatic and require much less attention. Because of this they may also be harder to describe. The question is an intriguing one and needs to be investigated with more precision than was done here. It may be that the most experienced analysts produce verbal rationales for their evaluations that are less trustworthy than those of their inexperienced colleagues!

D. Criticisms of the Experiment

When questioned about the task, several brokers felt that the factors and their levels were not descriptive enough. They would have preferred judging companies for which charts of support, resistance, and volume trends were given along with actual numbers representing the levels of profit margins, price/earnings ratios, etc. They also requested some information about current price and trading range of the stock. Still others felt that the type of client should have varied from one stock to another. The suggestions for more descriptive information could readily be accommodated within the restrictions of the ANOVA technique, and variation of the type of investor, as one of the cue factors, would lead to an interesting study of the manner in which the use of information changed from one type of client to the next.

V. Concluding Remarks

The principal results of the illustrative study, namely that strong individual differences in linear and configural use of information exist, can be made explicit, and can be contrasted with subjective perceptions, should be viewed as preliminary until further studies are completed. These studies should use more sophisticated analysts as subjects and more realistic cases as stimuli. Stimulus cases can be made more realistic, as noted above, by allowing factors to take more than two levels and by defining those levels in more descriptive terms. However, studies should also be done in which analysts judge real companies. Here, one does not have precise control over the distributions and interrelations of factors and these factors will undoubtedly be correlated across a set of companies. In these studies, multiple regression rather than ANOVA should be used as the data analysis model and it may not be possible to estimate configural effects with precision. However, it should be possible to make many of the same types of comparisons, using main effects, as were made above in the illustrative study.[20]

The results of the present study suggest that techniques such as ANOVA and multiple regression have considerable promise as devices for describing and furthering our understanding of the use of information in investment decisions. These techniques are likely to provide experts with new insight into their inferential processes. Furthermore, they might also be valuable teaching devices that would enable students to see exactly how their own processes differ from those of experts or optimal models.

One additional and rather remarkable benefit from quantitative analyses of judgment bears mentioning. Studies by Bowman, Kunreuther, and Goldberg have shown that, although mathematical models based on such analyses may not be optimal, the consistent application of these models often leads to decisions that are superior to those of the individuals who are being modeled.[21] This arises from the fact that humans tend to be erratic in their judgments, thus generating error that reduces their accuracy. The model filters out this error and is, therefore, able to outperform the decision maker whose judgments it was designed to simulate. The exciting implications of this discovery remain to be exploited.

Footnotes

*The authors are, respectively, Research Associate, Oregon Research Institute, Eugene, Oregon; Graduate Student, University of Oregon; and Professor of Finance, Graduate School of Management and Business, University of Oregon.

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1. A. Bernhard, The Evaluation of Common Stocks, New York: Simon & Schuster, 1959, p. 39.

2. See, for example, W. S. Bauman, "Scientific Investment Analysis," Financial Analysts Journal, Vol. 23, 1967, pp. 93-97.

3. G. P. E. Clarkson, Portfolio Selection: A Simulation of Trust Investment, Englewood Cliffs, N. J.: Prentice-Hall, 1962.

4. A similar research program intended to provide a rigorous understanding of the decision processes involved in granting loan applications is described in K. J. Cohen, T. C. Gilmore, and F. A. Singer, "Bank Procedures for Analyzing Business Loan Applications," in K. J. Cohen and F. S. Hammer, Analytical Methods in Banking, Homewood, Ill.: R. D. Irwin, 1966, pp. 218-251. Other attempts to analyze the judgment process in all its complexity are: B. Kleinmuntz, "The Processing of Clinical Information by Man and Machine," B. Kleinmuntz (Ed.), Formal Representation of Human Judgment, New York: Wiley, 1968, pp. 149-186; and H. J. A. Rimoldi, "The Test of Diagnostic Skills," Loyola Psychometric Laboratory Publication No. 25, Loyola University, Chicago, 1962.

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9. G. Loeb, The Battle for Investment Survival, New York: Simon and Schuster, 1965, p. 65.

10. The description of the analysis-of-variance model and techniques can only be given minimal coverage here. For more details, the reader should consult a standard textbook of statistics.

11. These categories could have more descriptive labels, however. For example, P/E Ratio could be categorized as below 10, between 10 and 20, and above 20.

12. We have been treating the cell entries in Table 1 as mean judgments. There will typically be variability around these means. This "within-cell" variability is usually regarded as sampling error. It is important to estimate whether an apparent effect is, or is not, due to error before deciding that something systematic is actually occurring. The analysis of variance is well known for its ability to test whether an effect is greater than could be attributed to error. If it is, we say that the effect is "statistically significant."

If a factor has n levels where $n > 2$, its main effect can be partitioned into a linear trend component and curvilinear components up to degree $n - 1$. Thus a significant linear trend in the main effect of Factor X would indicate that the best fitting polynomial equation to predict the judgments should include a linear function of X. If a significant quadratic trend appears in the main effect of Factor X, an X^2 term should be added to the equation, etc. For further discussion of this point see W. G. Cochran and G. M. Cox, Experimental Designs, New York: Wiley, 1957, pp. 335-375.

13. When two or more factors exhibit a significant interaction, a cross-product term involving those factors should be added to the mathematical model of the judge. See W. G. Cochran and G. M. Cox, op. cit., pp. 335-375.

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15. For details of how to construct such fractional replication designs see W. G. Cochran and G. M. Cox, op. cit., pp. 244-292.

16. The rationale and computing formulas for the ω^2 index are presented in W. L. Hays, Statistics for Psychologists, New York: Holt, Rinehart, and Winston, 1963, pp. 381-382 and 406-407.

17. The equation of the judge should, ideally, be cross-validated against a new sample of this judge's predictions. When this is done, one would expect some shrinkage in the percent of variance that the equation could predict. However, previous studies of judgment models have found the degree of shrinkage in such new samples to be tolerably small. For example, see N. Wiggins and P. J. Hoffman, "Three Models of Clinical Judgment," Journal of Abnormal Psychology, Vol. 73, 1968, pp. 70-77.

18. For further illustration and discussion of this point see Goldberg, op. cit., pp. 488-491; and D. B. Yntema and W. S. Torgerson, "Man-Computer Interaction in Decisions Requiring Common Sense," in W. Edwards and A. Tversky (Eds.), Decision Making, Baltimore: Penguin Books, 1967, pp. 300-314.

19. It is possible that the brokers were estimating subjective main effects only and that a new index that omitted the calculated effects of interactions would produce significantly higher correlations between subjective and computed importance. This hypothesis was tested and was not substantiated.

20. For examples of techniques and analyses that could be used with real companies, see Hoffman, op. cit., and Hammond, Hursch, and Todd, op. cit.

21. Bowman, op. cit.; Kunreuther, op. cit.; L. R. Goldberg, "Man versus Model of Man: A Rationale, Plus Some Evidence, for a Method of Improving on Clinical Inferences," Psychological Bulletin, Vol. 73, 1970, pp. 422-432.

Table 1

The Influence of a Main Effect for a Single Factor[a]

		Volume (2)			
		down (-)	up (+)	M_j ↓	
Support (1)	down (-)	3	3	3	$\alpha_- = 3 - 4 = -1$
	up (+)	5	5	5	$\alpha_+ = 5 - 4 = +1$
	M_k →	4	4	M= 4	

$\beta_- = 4 - 4 = 0$

$\beta_+ = 4 - 4 = 0$

---

[a]Cell entries are the mean judgments (M_{jk}) for all cases observed to be in condition j with regard to support level and condition k with regard to volume.

Table 2

An Additive Combination of Two Main Effects

Support \ Volume	down (-)	up (+)	M_j ↓
down (-)	1	5	3
up (+)	3	7	5
M_k →	2	6	M= 4

$\alpha_- = 3 - 4 = -1$

$\alpha_+ = 5 - 4 = +1$

$\beta_- = 2 - 4 = -2$

$\beta_+ = 6 - 4 = +2$

Computation of Cell Entries →

$$\underline{J_{ijk} = M + \alpha_j + \beta_k}$$

$$J_{i++} = 4 + 1 + 2 = 7$$

$$J_{i+-} = 4 + 1 - 2 = 3$$

$$J_{i-+} = 4 - 1 + 2 = 5$$

$$J_{i--} = 4 = 1 = 2 = 1$$

Table 3

A Two-Way Interactive Combination of Signs

		Volume (β)		
	down (-)	up (+)	M_j ↓	
Support (α) down (-)	3	3	3	$\alpha_- = -1$
Support (α) up (+)	1	9	5	$\alpha_+ = +1$
M_k →	2	6	M= 4	

$\beta_- = -2$

$\beta_+ = +2$

Interaction Effects →

$$\gamma_{--} = 3 - 3 - 2 + 4 = 2$$
$$\gamma_{-+} = 3 - 3 - 6 + 4 = -2$$
$$\gamma_{+-} = 1 - 5 - 2 + 4 = -2$$
$$\gamma_{++} = 9 - 5 - 6 + 4 = 2$$

Entry for Cell ++ $= J_{i++} = M + \alpha_+ + \beta_+ + \gamma_{++} = 4 + 1 + 2 + 2 = 9$

Table 4

The Relative Importance of the 8 Factors and Their Significant Interactions for Broker 2

Factor	Description of Levels		Mean Judgment		Magnitude of Effect[a]	Mean Square	% of Variance (ω^2)
	Level 1	Level 2	Level 1	Level 2			
Main Effects							
Industry (IND)	Stable	Dynamic	4.31	4.38	.07	.1	.00
Resistance Level (RES)	Up	Down	4.84	3.84	1.00	16.0*	.06
Support Level (SUPP)	Down	Up	3.53	5.16	1.63	42.3**	.19
Volume Trend (VOL)	Up	Down	4.53	4.16	.37	2.2	.00
Near Term Prospects (NTP)	Good	Poor	4.53	4.16	.37	2.2	.00
Profit Margin Trend (PMT)	Up	Down	4.50	4.19	.31	1.6	.00
Price/Earnings Ratio (PER)	Poor	Good	4.41	4.28	.13	.2	.00
Earnings Yearly Trend (EYT)	Down	Up	3.44	5.25	1.81	52.6**	.24
Interactions							
None							
Error						2.7	
Sum of effects over the statistically significant factors						(main effects)	.50
						(interactions)	.00
							.50

[a] Based on the degree to which the mean judgment changes as the level of the factor changes.

* $p < .05$

** $p < .01$

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Table 5

The Relative Importance of the 8 Factors and Their Significant Interactions for Broker 10

Factor	Description of Levels: Level 1	Description of Levels: Level 2	Mean Judgment: Level 1	Mean Judgment: Level 2	Magnitude of Effect[a]	Mean Square	% of Variance (ω^2)
Main Effects							
Industry (IND)	Stable	Dynamic	4.81	5.19	.38	2.2	.01
Resistance Level (RES)	Up	Down	5.12	4.88	.25	1.0	.00
Support Level (SUPP)	Down	Up	4.72	5.28	.56	5.1^{*}	.02
Volume Trend (VOL)	Up	Down	5.31	4.69	.62	6.2^{**}	.02
Near Term Prospects (NTP)	Good	Poor	6.19	3.81	2.38	90.2^{**}	.35
Profit Margin Trend (PMT)	Up	Down	5.59	4.41	1.19	22.6^{**}	.08
Price/ Earnings Ratio (PER)	Poor	Good	4.41	5.59	1.19	22.6^{**}	.08
Earnings Yearly Trend (EYT)	Down	Up	4.22	5.78	1.56	39.1^{**}	.15
Interactions							
IND x NTP					.75	9.0^{**}	.03
VOL x NTP					.75	9.0^{**}	.03
NTP x PER					.44	3.1^{*}	.01
VOL x EYT					.44	3.1^{*}	.01
RES x PMT					.44	3.1^{*}	.01
RES x SUPP x VOL					.44	3.1^{*}	.01
IND x SUPP x PMT					.75	9.0^{**}	.03
Error						0.6	
Sum of effects over the statistically significant factors						(main effects)	.70
						(interactions)	.13
							.83

[a]Based on the degree to which the mean judgment changes as the level of the factor changes.

$^{*}p < .05$

$^{**}p < .01$

Table 6

Calculation of the Importance of Effect Index for Broker 10

Factor	Main Effects	Interaction Effects: IND X NTP	VOL X NTP	NTP X PER	IND X VOL	RES X PMT	RES X SUPP X VOL	IND X SUPP X VOL	Sum	Index of Importance (%)
Industry (IND)	.38	+.75			+.44			+.75	2.32	13
Resistance Level (RES)	.25					+.44	+.44		1.13	06
Support Level (SUPP)	.56						+.44	+.75	1.75	10
Volume Trend (VOL)	.62		+.75		+.44		+.44	+.75	3.00	17
Near Term Prospects (NTP)	2.38	+.75	+.75	+.44					4.32	25
Profit Margin Trend (PMT)	1.19					+.44			1.63	09
Price/Earnings Ratio (PER)	1.19			+.44					1.63	09
Earnings/Share Yearly Trend (EYT)	1.56								1.56	09
									17.34	98[a]

[a] The deviation from 100 is due to rounding error.

Table 7

Comparison Between Importance of Effect and Subjective Weights

Across 13 Brokers and 5 Students

	Factor	Broker No. 1	2	3	4	5	6	7	8	9	10	11	12	13	Mean for Brokers	Student No. 1	2	3	4	5	Mean for Students
Importance of Effect	IND	02	01	09	09	07	03	10	04	04	13	10	14	03	07	03	10	14	04	12	09
	RES	12	18	06	01	15	01	09	13	14	06	13	01	03	09	01	11	01	08	05	05
	SUPP	20	28	06	05	07	11	06	15	07	10	21	02	06	11	03	04	06	05	01	04
	VOL	16	07	08	13	08	14	06	18	13	17	07	02	04	10	14	07	04	02	00	05
	NTP	16	07	27	34	13	14	25	16	22	25	09	11	15	18	13	07	15	14	00	10
	PMT	09	05	05	02	11	20	14	09	10	09	11	24	22	12	13	18	10	17	10	14
	PER	13	02	24	14	03	07	09	12	02	09	14	15	23	11	04	12	16	22	33	17
	EYT	12	32	14	22	36	31	21	13	28	09	14	32	24	22	48	29	34	29	39	36
Subjective Weight	IND	15	25	10	15	10	20	15	15	13	15	10	10	15	14	10	03	20	09	18	12
	RES	08	06	05	00	05	10	10	15	08	05	20	20	05	09	00	01	05	07	03	03
	SUPP	08	06	06	00	05	10	10	15	08	05	20	20	10	09	00	01	05	07	03	03
	VOL	12	20	09	20	10	15	15	05	15	15	20	15	10	14	20	05	15	10	03	11
	NTP	12	04	30	20	10	10	20	10	20	15	05	05	20	14	13	10	05	12	15	11
	PMT	10	04	05	05	10	15	07	15	05	10	05	10	10	08	08	25	10	12	15	14
	PER	20	10	15	20	10	05	15	15	11	20	10	05	15	13	09	20	20	20	22	18
	EYT	15	25	20	20	40	15	08	10	20	15	10	15	15	18	40	35	20	24	20	28

Note.--The highest entry in each column is underlined.

COMPANY NUMBER 22

Resistance Level

UP

Support Level

DOWN

Volume Trend

DOWN

Industry

STABLE

Near Term Prospects

Poor

INCOME STATISTICS

Profit Margin Trend

DOWN

PE Ratio Comparison

GOOD

Earnings/Share Yearly Trend

DOWN

1	2	3	4	5	6	7	8	9
Substantial Decrease				No Change				Substantial Increase

Figure 1. Example of a stimulus company. The response scale is at the bottom.

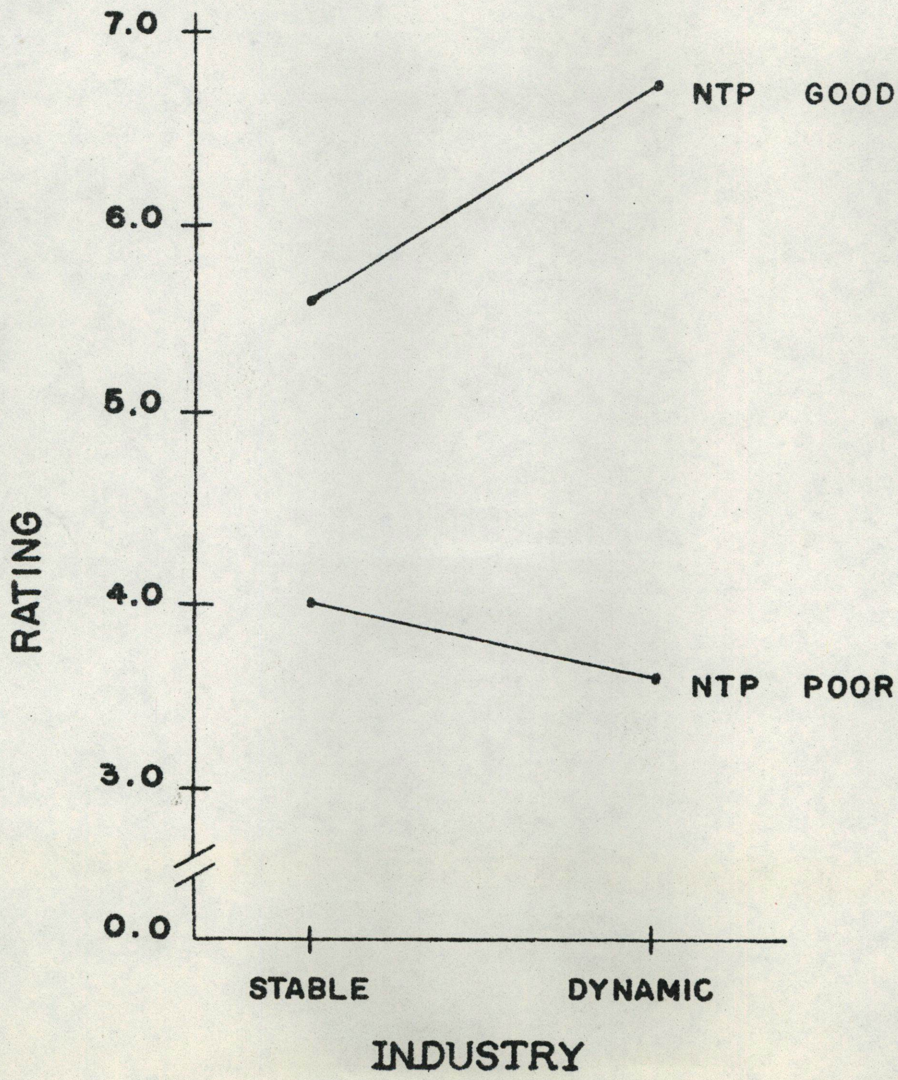

Figure 2. Graphical representation of the IND x NTP interaction effect for Broker 10.