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This paper reviews recent evidence bearing upon man's capabilities for integrating information into a judgment or decision. Among the topics discussed are studies of the accuracy and reliability of judgment; techniques for modeling the judgment process and making intuition explicit; biases in judgments of probability, variability, and correlation; experimental studies of individual and group risk-taking behavior; and relative merits of scientific versus intuitive approaches to information processing. Implications of this work for investment decision making are noted. Interdisciplinary studies of high-level decision makers and analysts, in their natural working environment, are recommended.

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Psychological Study of Human Judgment:

Implications for Investment Decision Making

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"You are--face it--a bunch of emotions, prejudices, and twitches, and this is all very well as long as you know it. Successful speculators do not necessarily have a complete portrait of themselves, warts and all, in their own minds, but they do have the ability to stop abruptly when their own intuition and what is happening Out There are suddenly out of kilter.

"If you don't know who you are, this is an expensive place to find out."

--Adam Smith - The Money Game

I. Introduction

Just as the stock market has been described as "The Money Game," security analysis, whether by expert or novice, might aptly be labeled "The Information Game." In no other realm are such vast quantities of information from such diverse sources brought to bear on so many important decisions. Careful accumulation and skilled interpretation of this information is said to be the *sine qua non* of accurate evaluation of securities.

The basic tenet of those in charge of helping the investor to make market decisions seems to be "the more information, the better." Bernhard, writing in 1959, noted that,

"Large brokerage houses undertook big advertising campaigns to acquaint investors with the 'research services.' Of what did the research consist? Primarily, it was represented as a careful compilation of all the facts deemed relevant to an understanding of the subject company and its stock. That done, the customer was left to his own devices to evaluate the facts [7; p. 34]."

Modern technology has contributed its share to the information explosion by making vastly greater quantities of elegant data readily available to the analyst, broker, and investor. However, little attention has been given to the problems of interpreting this information skillfully. Graham et al., in their classic treatise on security analysis, recognized the proper use of information as a key element of investment decision making. They observed, "After the analyst has learned what information he can get and where to get it, he faces the harder question: What use to make of it [30; p. 85]?"

Many aspects of investment analysis are said to be psychological in nature; certainly, the appraisal of man's capabilities for integrating information into a judgment or decision is one such aspect. Because of a lack of relevant psychological knowledge, security analysts have all too often been forced to become amateur psychologists themselves. For example, G. A. Drew asserted in 1941 that,

> "In fact, simplicity or singleness of approach is a greatly underrated factor of market success. As soon as the attempt is made to watch a multiplicity of factors, even though each has <u>some</u> element to justify it, one is only too likely to become lost in a maze of contradictory implications. . . . The various factors involved may be so conflicting that the conclusion finally drawn is no better than a snap judgment would have been [20; p. 86]."

Is Drew's speculation correct? What are man's limitations as a processor of information? The purpose of this paper is to acquaint the reader with psychology's recent endeavors to answer this general question. Along the way we shall touch on a number of related topics, including studies of the accuracy and reliability of judgment; techniques for modeling the judgment process and making intuition explicit; biases in judgments of probability, variability, and correlation; experimental studies of risk-taking behavior; and discussion of the relative merits of scientific versus intuitive approaches to making judgments and decisions. Wherever possible, implications of this work for investment decision making will be noted. If, as we proceed, we expose some warts, prejudices, and twitches, it is done in the belief that a full understanding of human limitations will ultimately benefit the decision maker more than will naive faith in the infallibility of his intellect.

II. Scientific vs. Subjective Prediction in Finance

To set the stage for a discussion of the relevant psychological literature, I would like to review briefly current opinion within the domain of investment analysis pertaining to the analyst's use of information.

The analyst is called upon to make predictions, forecasts, diagnoses, evaluations, etc., on the basis of fallible information, and with regard to such qualities as expected returns, growth rates, variability, and correlation. There is a branch of applied mathematics, namely statistics, whose purpose is to help men make these kinds of judgments. Most of the time, however, we bypass formal statistical procedures when making judgments, and when we do this we are acting as "intuitive statisticians."

The relative merit of scientific or statistical vs. subjective or intuitive methods of prediction is a controversial issue. The intuitive approach is the traditional and predominant method. Here decisions are seen as based more or less on a state of mind, on feelings or attitudes, on knowing, without the conscious use of well-defined reasoning. For example, consider the following quotations:

> ". . . this is no science. It is an art. Now we have computers and all sorts of statistics, but the market is still the same and understanding the market is still no easier. It is personal intuition, sensing patterns of behavior. . . [63; p. 20]."

> "What is it the good [money] managers have? It's a kind of locked-in concentration, an intuition, a feel, nothing that can be schooled [63; pp. 25-26]."

In the opposite corner are advocates of a scientific approach to investment analysis. Bauman [5] defines the scientific approach as one which consistently applies investment theory or a set of decision rules to a variety of investment situations, taking advantage of theoretically-derived or empirically-determined quantitative relationships between market factors and security performance. Although subjectivists criticize the scientific approaches as being too static and insensitive to subtle factors, scientific methods are rapidly gaining in popularity due to the availability of sophisticated mathematical and statistical techniques and the development of high-speed computers by which to implement them. Lorie [44] observed that a tremendous amount of research is in progress on such diverse subjects as insider trading, the effect of stock splits, portfolio selection, prediction of stock prices and earnings, etc. He concluded that much of this research work has already had the effect of discrediting beliefs--and even some relatively sophisticated ones--about the behavior of security prices.

Judgmental Accuracy in Investment Analysis

Gray [31] has recently warned security analysts that unless they develop procedures for measuring the validity of their efforts they are likely to have such assessments imposed upon them by those outside the profession. Despite the need for such appraisal, there have been relatively few attempts to assess the results of decisions made by analyst or investor under the harsh light of scientific scrutiny. And, in these investigations, the performance of man's inferences has appeared rather mediocre.

Cowles [16] made one of the first and most extensive attempts to determine the validity of "expert" forecasting. He found that sixteen financial services, making some 7500 recommendations on individual stocks between 1928 and 1932, compiled an average record that was worse than that of the average common stock by 1.4% annually. Cowles' close analysis of the forecasts of William D. Hamilton, editor of the Wall Street Journal, over the 26 years between 1904 and 1929, showed that they achieved a result poorer than a representative sample of stocks. Similarly, poor results were achieved by 24 financial publications between the years 1928 and 1932. A follow-up study in 1944 produced further negative findings along with the observation that more than 80% of all forecasts were bullish despite the fact that bear markets predominated during the period studied [17].

Treynor and Mazuy [64] evaluated the performance of 47 mutual funds and the sensitivity of their portfolio managers to market fluctuations. They reasoned that, if fund managers were able to anticipate major turns in the stock market, they would adjust the proportion of high and low-risk securities in their portfolios accordingly. Treynor and Mazuy found no evidence of such adjustments and they concluded that perhaps no investor, professional or amateur, can outguess the market. Several other investigations also indicate that the market has performed as well or better than a considerable number of professionally managed funds [4, 25, 35, 49, 69].

Perhaps the most extensive studies of the validity of individual investors' judgments are the several "Value Line Contests" in which individuals pit their own portfolios against those selected by Value Line and against the market averages. The 1969 contest attracted 65,000 entrants [48]. There appeared to be a greater number of superior portfolios among these than could be expected by chance. However, the majority of submitted portfolios were not analyzed in enough detail to permit a careful evaluation of contestants' abilities. Unfortunately, the results of two earlier Value Line Contests were also inconclusive regarding investors' ability to outperform the market averages [8, 32].

A study by Cragg and Malkiel [18] examined earnings projections for 185 corporations made by five different forecasting firms. The correlations between predicted and actual earnings turned out to be quite low, leading Cragg and Malkiel to conclude that the careful, painstaking efforts of the analysts performed little better than simple projections of past growth rates.

On the basis of this brief review, several conclusions seem warranted. First, there have still been relatively few studies concerned with the forecasting ability of sophisticated investors and analysts. Second, even these studies have not directly addressed the subjective vs. scientific issue. For example, the extent to which the analysts and fund managers evaluated by Cragg and Malkiel, Cowles, or Treynor and Mazuy used statistical as opposed to intuitive methods, is not known. With the exception of Cowles' work, interest in these issues is of relatively recent origin. In contrast, these and related questions have been studied extensively for several decades within psychology and medicine. The following discussions of relevant psychological research may place the results from securities analysis into broader perspective while suggesting worthwhile avenues for further investigation.

III. Psychological Studies of Human Judgment

Psychologists have a dual reason for studying the types of judgmental processes involved in stock market decisions. First, such processes are obviously within the proper domain of psychological inquiry. Second, clinical psychologists are forced to use much of the same sorts of processes in their role as diagnosticians of mental disorders and predictors of human behavior. Much of the psychological research relevant to investment decision making comes from the study of the judgmental processes of clinical psychologists, i.e., "clinical judgment." For a comprehensive review of research on clinical judgment see Goldberg [28].

Accuracy and Reliability of Clinical Judgment

Over the past 20 years, numerous studies have tested the accuracy of clinical judgments. The results, like those of investment judgments, have been quite discouraging. Goldberg references nine studies that not only demonstrated a marked lack of validity but also yielded the surprising finding that the judge's length of professional training and his experience often showed little relationship to his accuracy. Equally disillusioning are the 15 experiments cited by Goldberg which showed that the amount of information available to the judge was not necessarily related to the accuracy of his inferences. Typical of these is a study by Oskamp [50] who had 32 judges, including eight experienced clinical psychologists, read background information about a patient's case. The information was divided into four sections. After reading each section of the case, the judge answered 25 questions about the personality of the subject. The correct answers were known to the investigator. The clinician also rated his confidence in his answers. Oskamp found that, as the amount of information about the case increased, accuracy remained at about the same level while the clinicians' confidence increased dramatically and became disproportionately great. These findings may explain, in part, the prevailing tendency to provide the investment decision maker with as much information as possible. It makes him feel more confident, but will it improve his decision? This type of study would seem worth replicating within the context of security analysis.

The lack of validity of clinical judgments has led to a number of studies of their reliability. Goldberg distinguished between three types of reliability: (a) consistency, or stability across time for the same judge using the same data; (b) consensus, or agreement across judges using the same data; and (c) convergence, or agreement when one judge makes several judgments of the same case but uses different data each time. Studies reviewed by Goldberg indicate that consistency tends to be moderately high but consensus and convergence leave much to be desired. The reliability of investment forecasts would seem to merit systematic study. For one such attempt see [18].

Even in medicine, studies of clinical judgment have often revealed a surprising degree of unreliability and inaccuracy. Bakwin [3] reported an experiment which showed that there was no correlation whatsoever between the estimate of one physician and that of another regarding the advisability of tonsillectomy. These and similar results prompted Bakwin to conclude that, although the superstitions and magic rites that prevailed in the 17th Century had largely been forgotten, theories and practices persisted in the scientific era of medicine even though their falisty was patent. Garland [27] has provided similar and more recent examples of unreliability and inaccuracy in medicine. For example, numerous studies of radiologists showed that they failed to recognize the presence of lung disease about 30 percent of the time when reading X-rays. This was disease that was definitely visible on the X-ray film. They also found that a radiologist changed his mind about 20 percent of the time when reading the same film on two occasions.

This work in psychology and medicine, along with the previously described research in finance, implies that we must never take for granted the reliability and accuracy of a judge, no matter how expert. Whenever possible, empirical studies should be conducted to determine whether judgmental performance is satisfactory.

Clinical vs. Statistical Prediction

When one considers the typical findings of unreliability, lack of validity, and insensitivity to information, it is not surprising to find clinical judgments increasingly under attack by those who wish to substitute statistical prediction systems for the human judge. Thus psychology has its own version of the scientific vs. subjective controversy. This issue was popularized by Meehl's classic book titled Clinical vs. Statistical Prediction which was published in 1954 [47]. Goldberg [28] summarized the vast amount of research stimulated by Meehl's book by pointing out that over a very diverse array of clinical tasks, some of which were selected to show the clinician at his best and the statistician at his worst, rather simple actuarial formulae typically performed at least as well as the clinical expert. All this, of course, pertained to repetitive situations where historical data existed for the statistician to use. It would be interesting to pit clinical vs. statistical prediction methods in investment situations, although it is unlikely that the statistician's superiority would be any less there than in the many studies in clinical psychology. Recent studies by Sawyer [53], Pankoff and Roberts [51], and Einhorn [24] indicate that a combination of clinical and statistical methods, with the clinician gathering the data and the statistician processing it, may be the optimal procedure to follow in many judgment situations.

Descriptive Analysis of the Judgment Process

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 [7] observed that, if the mental process of consistently successful investors are intuitional, that intuitional reasoning must be made understandable. In a similar vein, Bauman [5] has 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.

Researchers in the areas of economics, finance, and psychology have recently taken up the challenge of simulating and describing the judgment process. At present, there are a number of new methods that should be of interest to persons concerned with the dynamics of investment decisions.

Complex simulation. It is interesting that some of the most important analyses of complex judgment processes were undertaken within the context of financial decision making. Perhaps the outstanding example is the work of Clarkson [12] who undertook to simulate the portfolio selection processes of a bank's trust investment officer. Clarkson followed the officer around for several months and studied his verbalized reflections as he was asked to think aloud while reviewing past and present decisions. Using these verbal descriptions 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 future portfolios selected by the trust officer, the correspondence between actual and simulated portfolios was found to be remarkably good. A similar research plan designed to simulate the decision processes of bank officers when granting business loans was outlined by Cohen, Gilmore, and Singer [14].

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, there is still 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 Clarkson's complex, sequentially branching model and the relatively naive approaches of the pre-computer era--such as simply asking the decision maker how he makes his judgments. The rationale behind these mathematical models and techniques for building them are reviewed by Slovic and Lichtenstein [61].

The basic approach requires the decision maker to make quantitative 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, one could also fit a regression equation to the analyst's judgments to capture his personal weighting policy. The resultant equation would be:

$$\hat{J}_{pa} = b_1X_1 + b_2X_2 + \ldots b_kX_k \tag{1}$$

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 predicting judgments of such diverse phenomena as psychiatric diagnoses, malignancy of ulcers, job performance, and the riskiness and attractiveness of gambles; and political scientists have found linear models useful for describing judicial decision processes in workmen's compensation and civil liberties court cases [61]. Researchers interested in simulating financial and managerial decisions have independently discovered the value of linear models. For example, Bowman [9] and Kunreuther [38] successfully fit linear models to decisions concerned with production scheduling and Hester [33] used regression analysis to develop a "loan offer function" representative of the lending policy of a particular bank. Hester's function makes explicit the weighting of such factors as the applicant's profits, his deposit balance, his current ratio of assets to liabilities, etc. Such a function could be compared with the bank's formally-stated policy guidelines. Functions of different loan officers could also be compared.

Large individual differences among weighting policies have been found in almost every study that reports individual equations. A striking example of this in a task demanding a high level of expertise comes from a study of nine radiologists by Hoffman, Slovic, and Rorer [34]. The stimuli were ulcers, described by the presence or absence of seven roentgenological signs. Each ulcer was rated according to its likelihood of being malignant. There was considerable disagreement among radiologists' judgments, as indicated by a median interjudge correlation, across stimuli, of only .38. Examination of each radiologist's linear equation clearly pinpointed the idiosyncratic weightings of the various signs that led to the observed disagreements in diagnosis.

Nonlinear models. Although the linear model does an impressive job of predicting judgments, when one asks individuals how they are processing information their comments suggest that they use cues in a variety of nonlinear ways. Researchers have attempted to capture these nonlinear processes by means of more complex equations. One type of nonlinearity occurs when an individual cue relates to the judgments in a curvilinear manner. For example, this quote from Loeb suggests a curvilinear relation between the volume of trading on a stock and its future prospects:

> "If you are driving a car you can get to your destination more quickly at 50 mph than at 10 mph. But you may wreck the car at 100 mph. In a similar way, increasing volume on an advance up to a point is bullish and decreasing volume on a rally is bearish, but in both cases only up to a point [43; p. 287]."

Curvilinear functions such as this quote suggests can be modeled by including exponential terms (i.e., X_i^2, X_i^3, etc.) as predictors in the judge's policy equation.

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. This 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 . . . [43; p. 65]."

Since analysts believe that factors relevant to investment decisions should often be interpreted configurally, 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. Thus, if the meaning of factor X_1 varies as a function of the level of factor X_2, the term $b_{12}X_1X_2$ can be added to the equation. A number of studies have employed a statistical technique, analysis of variance, to identify configural processes in judgment. For example, Slovic, Fleissner, and Bauman [59] used this technique to isolate configural processes used by stockbrokers when evaluating the attractiveness of common stocks. A number of interesting instances of configural uses of information were found in these studies and large differences in the policy equations for individual brokers were also evident.

Subjective Weights and Self-Insight

Thus far we have been discussing weighting policies that have been assessed by fitting an algebraic model to the judge's responses. We think of these as "computed" or "objective" policies. Judges in a number of studies were asked to estimate the relative weights they had been using in the task. The correspondence between these "subjective weights" and the computed weights indicated the judge's insight into his own policy. One type of error in self-insight has emerged in all of these studies [61]. Judges strongly overestimate the importance they place on minor cues (i.e., their subjective weights greatly exceed the computed weights for these cues) and they underestimate their reliance on a few major variables.

In a recent study of 13 stockbrokers, Slovic, Fleissner, and Bauman [59] found an intriguing result that needs to be tested further. The longer a broker had been in the business, the less accurate was his insight into his weighting policy.

<u>Bootstrapping</u>. Can a system be designed to aid the decision maker that is based on his own judgments of complex stimuli? One possibility is suggested by the finding that algebraic models, such as the linear model, can do a remarkably good job of simulating such judgments. An important hypothesis about cooperative interaction between man and machine is that the model of the man may be able to make better predictions than the man himself. Dawes [19] has termed this phenomenon "bootstrapping."

The rationale behind the bootstrapping hypothesis is quite simple. Although the human judge possesses his full share of human learning and hypothesis-generating skills, he lacks the reliability of a machine. As Goldberg [29] has noted:

"He is subject to all these human frailties which lower the reliability of his judgments below unity. And, if the judge's reliability is less than unity, there must be error in his judgments--error which can serve no other purpose than to attenuate his accuracy. If we could . . . [eliminate] the random error in his judgments, we should thereby increase the validity of the resulting predictions [29; p. 423]."

The algebraic model captures the judge's weighting policy and applies it consistently. If there is some validity to this policy to begin with, filtering out the error via the model should increase accuracy. Of course, bootstrapping preserves and reinforces any misconceptions or biases that the judge may have. Implicit in the use of bootstrapping is the assumption that these biases will be less detrimental to performance than the inconsistencies of unaided human judgment.

Bootstrapping has been explored independently by a number of different investigators. Bowman [9] outlined a bootstrapping approach within the context of managerial decision making that has stimulated considerable empirical research. Other applications of bootstrapping have been described by Dawes [19], Goldberg [29], and Wiggins and Kohen [70].

Studies of Probabilistic Inference

Conservatism. There is a rapidly developing school of thought called "Decision Theory" which asserts that we ought to cast our opinions about the world in probabilistic terms [22, 52]. For example, rather than predicting that a stock will sell at a specific price six months from now, we should estimate a probability distribution across a set of possible prices. These probabilities can then be used, in combination with information about the payoffs associated with various decisions and states of the world, to implement any of a number of decision rules, including the maximization of expected value or expected utility.

When we translate our opinions into probabilities, a mathematical formula, Bayes' theorem, dictates the optimal way that our estimates should change upon receipt of new information. Led by the efforts of Edwards [22, 23], many psychologists have compared man's subjective probability revisions with those of Bayes' theorem in a variety of experimental and real-life situations. This research shows that men are conservative processors of fallible information. Upon receipt of new data, subjects revise their probability estimates in the direction prescribed by Bayes' theorem, but the revision is typically too small; subjects respond as though the data are less diagnostic than they truly are. In some studies subjects have required from two to nine data observations to revise their estimates as much as Bayes' theorem would prescribe after just one observation. A number of experiments have attempted to explain this finding. The results are controversial, but in Edwards' view [21] the major cause of conservatism is human misaggregation of the data. That is, men perceive such datum accurately and are well aware of its individual diagnostic meaning, but are unable to combine its meaning properly with their prior opinions and with the diagnostic meaning of other data when revising their estimates.

Intuitions about sampling variability. There is a different type of probabilistic inference in which decision makers turn out to be very nonconservative. This work is described by Tversky and Kahneman [65] who analyzed the decisions psychologists made when planning their scientific experiments. Despite formal training in statistics, psychologists usually rely upon their educated intuitions when they decide how large a sample of data to collect or whether they should repeat an experiment to make sure their results are reliable. Tversky and Kahneman distributed a questionnaire to psychologists in the audience at the meetings of several professional societies. Typical of the questions was the following:

"Suppose you have run an experiment on 20 subjects, and have obtained a significant result which confirms your theory ($z=2.23$, $p<.05$, two-tailed). You now have cause to run an additional group of 10 subjects. What do you think the probability is that the results will be significant, by a one-tailed test, separately for this group [p. 105]?"

From the answers to this and a variety of other questions, Tversky and Kahneman concluded that people have strong intuitions about random sampling; that these intuitions are wrong in fundamental ways; that they are shared by naive persons and sophisticated scientists alike; and that they are applied with unfortunate consequences in the course of scientific inquiry. They found that the typical scientist gambles his research hypotheses on small samples without realizing that the odds against his obtaining accurate results are unreasonably high; has undue confidence in early trends from the first few data points and in the stability of observed patterns; has unreasonably high expectations about the replicability of significant results; and rarely attributes a deviation of results from expectations to sampling variability because he finds a causal explanation for any discrepancy.

Tversky and Kahneman summarized these results by asserting that people's intuitions seemed to satisfy a "law of small numbers" which means that the "law of large numbers" applies to small samples as well as to large ones. The "law of large numbers" says that very large samples will be highly representative of the population from which they are drawn. Thus, small samples were also expected to be highly representative of the population. Since acquaintance with logic or probability theory did not make the scientist any less susceptible to these cognitive biases, Tversky and Kahneman concluded that the only effective precaution is the use of formal statistical procedures, rather than intuition, to design experiments and evaluate data.

In a related study of college undergraduates, Kahneman and Tversky [36] found that many of these individuals did not understand the fundamental principal of sampling, i.e., the notion that the error in a sample becomes smaller as the sample size gets larger. Kahneman and Tversky concluded: "For anyone who would wish to view man as a reasonable intuitive statistician, such results are discouraging [p.]."

Biases in Judgments of Probability, Variability, and Covariation

What can be done to help the decision maker interpret and combine information appropriately? Bootstrapping is one answer to this question. Most of the other answers involve some version of the decomposition principle:

> "The spirit of decision analysis is divide and conquer: Decompose a complex problem into simpler problems, get your thinking straight in these simpler problems, paste these analyses together with a logical glue, and come out with a program for action for the complex problem. Experts are not asked complicated, fuzzy questions, but crystal clear, unambiguous, elemental, hypothetical questions [52; p. 271]."

There seems to be general agreement that we cannot do away with the human element in judgment, so the decomposition approach attempts to obtain relatively simple judgments that can be integrated by some optimal combination model. In this way, it relieves the judge from having to integrate his basic opinions and expectations. For example, certain information-processing systems require men to estimate the probability that each of various items of data would be observed, given a certain state of the world. These estimates are then processed mechanically via Bayes' theorem to produce an estimate of the probability of that state, given that this data was observed [22, 23]. In the realm of finance, portfolio selection models require that analysts estimate expected returns, variances, covariances, etc., which are then combined via an optimal model [1, 46]. Similarly, models of common stock valuation require an analyst to make estimates of future balance-sheet and income data, which can be combined by an empirically-derived or theoretically-based model [1, 68]. The use of decision trees to analyze complex investment problems is another example of decomposition [45, 52].

Decomposition is certainly a reasonable approach, although it is still too early to know how successful it will be. Critics claim that the decision maker may be able to make good judgments and choices without being able to introspect accurately about the values and expectations that underlie his actions. A decision maker who has developed an expertise in a particular area may find it extremely difficult and unnatural to respond to elemental questions about which he has never thought and with which he has had no direct experience. In addition, there are a number of biases that distort even the simplest kinds of judgments of probability, variance, or correlation, as the remainder of this section will illustrate.

<u>Biased judgments of probability.</u> Some of the inadequacies of probabilistic judgment have already been discussed. In addition to conservatism and the belief in the law of small numbers, there is yet another source of

distortion, "availability bias," that affects simple probability estimates. According to Tversky and Kahneman [66], the essence of this bias is that judgments of an event's probability are determined by the number of instances of that event that are remembered and the ease with which they come to mind. The availability of instances is affected by such factors as recency, salience, and imaginability, all of which may or may not be related to the correct probability. For example, the letter k is three times as likely to appear as the third letter of an English word as the first letter, yet most persons judge it as more likely to be a first letter. Tversky and Kahneman hypothesize that, when subjects make this judgment, they try to think of words either beginning with k or having k as a third letter. It is easier to think of words that begin with k, and if we use that fact as a cue on which to base our intuitive probability estimates, these words will be perceived as more probable than words with k in the third position. In general, the harder it is to recall or imagine instances of an event, the lower the judged probability of that event.

The effects of availability bias are not likely to be limited to the psychological laboratory. An analyst who attempts to evaluate the likelihood of a recession may do so by recalling economic conditions similar to those of the present or by recalling recessions. The latter are easier to retrieve because they are more sharply defined, whereas states of the economy are more difficult to characterize and, therefore, harder to remember. The resulting probability estimate is likely to be greatly dependent upon which of these two mental sets the analyst adopts. Even the form of the question may be important. Consider the following questions:

a) "How likely is it that there will be a recession soon?"

b) "How likely is it that, with the present tightening of credit, there will be a recession soon?"

The first question may focus attention on past instances of recession, whereas the latter may cause the analyst to think about previous credit conditions.

There are numerous other instances of systematic biases in our judgments of probabilities. Cohen and Chesnick [13] and Slovic [57] found that subjects systematically misperceived the probabilities of compound events. For example, in the study by Cohen and Chesnick, some people preferred the opportunity of drawing a winning lottery ticket out of a population of 10 tickets (with one attempt) to the chance to draw the winner out of 100 tickets, even when they had up to twenty draws of the latter kind (with replacement after each draw). Other studies have found that the desirability of an event biases its subjective probability [55], although the effects are complex and differ from person to person. Some people are overly optimistic, tending to attribute greater probability to highly-desired events than to undesired events, other factors being equal. Other persons consistently overestimate the likelihood of unpleasant events.

Biased judgments of variance. Several factors seem to influence a person's judgment of the variance of a sequence of values about the mean of that sequence [6, 39]. The first of these factors is the mean itself. Perceived variance increases as the mean decreases. A standard deviation of two feet for a group of saplings would be perceived as larger than the same standard deviation for a group of fully-grown trees. Greater irregularity in a sequence also leads to an illusion of greater variance. Sequences in which the values progress in an orderly fashion (e.g., ascending or descending or ascending up to a point, then descending, etc.), with little difference between successive values, are perceived to have less variance than sequences whose adjacent values are less regular [39]. The stimuli in experiments on perceived variance have been sets of line lengths and numbers. It would be interesting to determine whether these same sorts of biases would occur when the variance of a sequence of stock prices or earnings reports was being judged.

Biased judgments of correlation and causality. There have been a number of studies relating to judgments of correlation and causality. The results of these studies suggest that even if the random walk theory of security price changes were absolutely ture, we probably would not believe it and would find, upon observing random price changes, what appear to be meaningful patterns upon which to base our forecasts.

Several lines of psychological research appear relevant here. The first stems from a classic experiment by Skinner [54]. Skinner found that hungry birds, given food at brief random intervals, developed very idiosyncratic, repetitive actions. The precise form of this behavior varied from bird to bird, and Skinner referred to these actions as superstitions. What happened to these birds can be described in terms of the concept of positive reinforcement. The delivery of food increased the likelihood of whatever form of behavior happened to precede it. Food was then presented again. Because the reinforced behavior was occurring at an increased rate, it was more likely to be reinforced again. The second reinforcement caused a further increase in the rate of this particular behavior which improved its chances of being reinforced again, and so on. After a short while the birds were found to be turning rapidly counter-clockwise about the cage, hopping from side to side, making odd head movements, etc. Because such behaviors are reinforced less than 100 percent of the time during learning, they persist even when reinforcement stops altogether. Animals trained in this way have been known to make as many as 10,000 attempts to obtain a reward that was no longer forthcoming.

The environment of the stock market seems to provide exactly the right conditions for the development and maintenance of superstitious behavior. That is, there has been a favorable expected return and thus a predominance of positive reinforcement (at least in the past) which is administered intermittently. And there is always the hope that if enough people harbor the same superstitions, and the game is to anticipate the actions of the crowd, then knowing the superstitions and acting on them may be quite rewarding. At any rate, one chartist may have been correct when he said, "If I hadn't made money some of the time, I would have acquired market wisdom quicker [40, p. 30]."

The superstitions developed in Skinner's pigeons were highly individualistic. Yet the behavior and the lore of Wall Street is often commonly agreed upon. How can this consensus be reconciled with the notion of stock-price changes as a random walk? Several recent experiments by Chapman and Chapman [10] may provide a possible answer to this question along with further insight into the pitfalls awaiting human intuition.

The Chapmans, studying a phenomenon they have labeled illusory correlation, have shown how our prior expectations of relationships can lead to faulty observation and inference, even under seemingly excellent conditions for learning. They presented naive subjects with human figure drawings, each of which was paired with a statement about the personality of the patients who allegedly drew the figures. These statements were randomly paired with the figure drawings so that the figure cues were unrelated to the personality of the drawer. They found that most subjects learned to see what they expected to see. In fact, naive subjects discovered the same relationships between drawings and personality that expert psychologists report observing in their clinical practice, although these relationships were absent in the experimental materials. The illusory correlates corresponded to commonly-held expectations, such as figures with big eyes being drawn by suspicious people, muscular figures being drawn by individuals who worried about their manliness, etc.

The Chapmans noted that in clinical practice the observer is reinforced in his observation of illusory correlates by the reports of his fellow clinicians, who themselves are subject to the same illusions. Such agreement among experts is, unfortunately, often mistaken as evidence for the truth of the observation. They concluded that the clinician's cognitive task may exceed the capacity of the human intellect and they suggested that subjective intuition may need to be replaced, at least partially, by statistical methods of prediction.

The research on illusory correlation suggests parallel experiments using stock prices. One hypothesis is that, if we provide a stream of random price changes to intelligent but naive subjects, say undergraduate students in a finance course, they might discover in these random sequences some of the same rules that we see accepted by chartists or other analysts. Although the influence of illusory correlation in financial analysis remains to be demonstrated, there is no reason to believe that it will be less here than in clinical psychology.

Finally, a number of studies have investigated subjects' perceptions of correlation and causality in simple situations involving just two binary variables. Consider a 2 x 2 table of frequencies in which variable A is the antecedent or input variable and B is the consequent or output variable:

	B_1	B_2
A_1	$A_1B_1 = a$	$A_1B_2 = b$
A_2	$A_2B_1 = c$	$A_2B_2 = d$

A correlation or contingency exists between A and B to the extent that the probability of B_1 given A_1 differs from the probability of B_1 given A_2: that is, to the extent that $a/(a + b)$ differs from $c/(c + d)$.

Research indicates that subjects' judgments of contingency are not based on a comparison of $a/(a + b)$ versus $c/(c + d)$. For example, Smedslund [62] had students of nursing judge the relation between a symptom and the diagnosis of a disease. He found that the judgments were based mainly on the frequency of joint occurrence of symptom and disease (cell a in the matrix), without taking the other three event combinations into account. As a result, the judgments were unrelated to actual contingency. Similar results were obtained by Ward and Jenkins [67] who concluded:

> "In general . . . statistically naive subjects lack an abstract concept of contingency that is isomorphic with the statistical concept. Those who receive information on a trial by trial basis, as it usually occurs in the real world, generally fail to assess adequately the degree of relationship present [67; p. 240]."

IV. Experimental Study of Risk-Taking Behavior

There is a great deal of experimental research on risk-taking behavior that may have implications for investment decision making. In this research, subjects are asked to indicate their preferences and opinions among various gambles. Gambles are studied because they represent, in abstract form, important aspects of real-life decisions--namely, probabilities, incentives, and risks. By using gambles, the basic dimensions of risk-taking situations can be manipulated and hypotheses can be tested in a rigorous way. Whether the results generalize to real-life gambles must, of course, be checked by further research.

The Influence of Variance on Risk Taking

Theorists such as Allais [2], Fisher [26], and Markowitz [46] have argued that the variance of returns on an investment should be considered as an investment criterion in addition to the mean, or expected return. High variance is typically equated with high risk.

Does variance influence the perceived attractiveness of a gamble? Subjects in several psychological experiments have exhibited what seemed to be strong preferences for playing high or low varaince gambles [for example, see 16]. However, recent evidence suggests that the subjects in these experiments were choosing according to decision rules such as "minimize possible loss" or "maximize possible gain," rather than basing their preferences on variance per se. Variance appears to have correlated with the preferences only because it also correlated with these other strategies [60].

Another study has found that perceived risk was not a function of the variance of a gamble [56]. Instead, riskiness was more likely to be determined by the probability of loss and the amount of loss. This result is in accord with comments made by Lorie [44] who complained that it was absurd to call a stock risky because it went up much faster than the market in some years and only as fast in other years, while a security that never varies in price is not risky at all, if variance is used to define risk. The importance of understanding how risk is perceived is stressed by Lepper [41], who pointed out the crucial role of investors' perceptions of risk in determining the impact of various taxes. Taxes, of course, can alter markedly the variance of the potential returns for an investment.

Response Mode and Information Use

A study by Lichtenstein and Slovic [42] found that subtle changes in the manner in which the decision maker reported his evaluation of a gamble had a strong influence on the way that he processed information about probabilities and payoffs. For example, consider the following pair of bets:

Bet A: .90 to win $ 4 and .10 to lose $2

Bet B: .30 to win $16 and .70 to lose $2.

Bet A has a much better probability of winning but Bet B offers a higher winning payoff. Lichtenstein and Slovic's subjects were shown many such pairs of bets. They were asked to indicate, in two ways, how much they would like to play each bet in a pair. First they made a simple choice, A or B. Later they were asked to assume they owned a ticket to play each bet, and they were to state the lowest price for which they would sell this ticket.

Presumably these selling prices and choices are both governed by the same underlying quality, the subjective attractiveness of each gamble. Therefore, the subject should state a higher selling price for the gamble that he prefers in the choice situation. However, Lichtenstein and Slovic found that subjects often chose Bet A, yet stated a higher selling price for Bet B. Why should this happen? Lichtenstein and Slovic have traced it to the fact that subjects used different cognitive strategies for setting prices than for making choices. Subjects choose Bet A because of its good odds, but they set a higher price for B because of its large winning payoff.

A "compatibility" effect seemed to be operating here. Since a selling price is expressed in terms of monetary units, subjects apparently found it easier to use the monetary aspects of the gamble to produce this type of response. Such a bias did not exist with the choices since each attribute of one gamble could be directly compared with the same attribute of the other gamble. With no reason to use payoffs as a starting point, subjects were free to use any number of strategies to determine their choices. In most cases, they relied primarily on the probabilities of winning and losing. When faced with their inconsistent decisions, many subjects had a very hard time changing either of their conflicting responses. They felt that the different strategies they used for each decision were appropriate. However, strict adherence to an inconsistent pattern of prices and choices can be termed irrational, since the inconsistent subject can be led into purchasing and trading gambles in such a way that he continually loses money.

The message in this research is that integrating information is quite a difficult cognitive task, and there may often be a very subtle interaction between the form of the information we have to use and the form of the judgmental response we have to make. This may well generalize beyond experimental gambling situations. For example, a financial analyst who is forecasting a stock's market price six months hence might be led to overweight previous price information, simply because of the compatibility factor. And if he was asked to forecast percentage price increase rather than price itself, he might then give more weight to other variables in the company report that were expressed in terms of percentages. Experiments testing this hypothesis would seem to be worth conducting, so that steps could be taken to minimize compatibility biases if they are found.

Is Willingness to Take Risks a Stable Personality Trait?

An understanding of risk-taking propensity as a personality characteristic could prove valuable in the selection and training of portfolio managers, investment couselors, or brokers. It would also help these individuals to better understand and service their clients. Although knowledge of the dynamics of risk taking is still limited, there is one important aspect that has been fairly well researched--that dealing with the stability of a person's characteristic risk-taking preferences as he moves from situation to situation. Typically, a subject is tested in a variety of risk-taking tasks involving problem solving, athletic, social, vocational, and pure gambling situations. The results of close to a dozen such studies indicate little correlation, from one setting to another, in a person's preferred level of risk taking [58]. Only those tasks highly similar in structure and involving the same sorts of payoffs (e.g., all financial, all social, etc.) have shown any generality and, as similarity decreases, these cross-task consistencies rapidly decline. Thus an individual who takes risks by guessing often on a mathematics exam (when guessing is penalized) is likely to be a high risk taker in other exams as well, but that does not imply that he would prefer a high-risk occupation. In sum, the majority of evidence argues against the existence of risk-taking propensity as a generalized characteristic of individuals. A person's previous learning experiences in specific risk-taking settings seem much more important than his general personality characteristics.

As an example of one implication of this work, consider the problem of selecting a portfolio manager. Suppose that one desires a manager who has the propensity to invest at high levels of risk. The best predictor of this characteristic would be the individual's demonstrated performance in a position highly similar to the one under consideration. Evidence of his risk-taking propensity gleaned from other forms of behaviors is unlikely to predict how he would behave in an investment situation.

Comparison of Group and Individual Risk Taking

Many decisions are made not by individuals, but by groups. Over the past decade, comparison of group versus individual risk-taking tendencies has been the subject of an extensive body of research. The typical finding is that decisions made by groups are riskier than the average of the individual members' decisions prior to group discussion. Individual risk-taking levels also increase following group discussion. This phenomenon has been labeled the "risky shift."

One of the leading explanations of the risky shift is the "diffusion of responsibility" hypothesis. It asserts that each group member feels less personal blame if his choice fails, thus he is not afraid to recommend or accept riskier courses of action.

Another explanation of the risky shift is the "cultural value" hypothesis which assumes that moderate riskiness is a stronger, more widely held cultural value than caution. This value leads individuals to perceive themselves as being at least as willing as their peers to take risks. In this regard, the group discussion provides information that allows group members to compare their own positions with those of their peers. Members whose initial positions were less risky than those of the group average come to learn that they are not as risky as they thought and as they want to be. To remedy this, they increase their level of risk taking.

Both of these explanations, and others as well, have received experimental verification. For more detailed discussion of group influence on risk taking see reviews by Clark [11] and Kogan and Wallach [37].

V. Concluding Remarks

Several facts are important about the research described in this paper. First, most of the work is of very recent origin. Second, with only a few exceptions, this research has been done without explicit consideration of problems in business and finance. As a result, there is a great need to replicate the various types of studies in specific financial settings. Studies of high-level decision makers and analysts, in their natural working environment, are particularly needed. Besides contributing to the understanding of financial decisions, such research would also benefit psychology, much as Clarkson's simulation of the trust investment officer provided important insight into the nature of complex thought processes. Obviously, this kind of research would benefit greatly from interdisciplinary collaboration among psychologists, economists, financial analysts, computer scientists, and others.

If research in financial settings verifies the early indications of man's information-processing limitations, the next phase of research must certainly emphasize the development of techniques to help decision makers overcome their cognitive biases. Will informing an analyst about his biases make him less susceptible to them or will it lead him to overcompensate, perhaps with even greater error? Would computer simulation be effective in conveying an appreciation of sampling variability and probabilities? The past decade of research has uncovered some fascinating questions. The next decade should provide some extremely interesting and important answers.

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