AN APPLICATION OF MULTIDIMENSIONAL SCALING TO THE
CONSTRUCTION OF PREDICTIVE PORTFOLIO SELECTION MODELS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for
the Degree Doctor of Philosophy in the Graduate
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by
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* * * * *

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To many individuals, but especially to my wife and my mother, this dissertation is dedicated.
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CHAPTER I
INTRODUCTION

Most modern normative portfolio selection models are based on the pioneering work of Markowitz.¹ Although important extensions and modifications of his ideas have been reported in recent years (especially by Sharpe,² Lintner,³ Jensen,⁴ and others), the basic Markowitz portfolio selection framework has remained intact. That is, investors are advised to utilize some version of the two-dimensional, mean-variance approach in which individual securities and portfolios are evaluated in terms of a trade-off between expected returns and expected variance of returns (a risk measure) over the relevant time horizon.

The primary objective of this research, however, is not the extension of normative portfolio theory beyond its current state. Rather, the purpose is to assess the degree to which well-known normative models of the mean-variance type actually reflect the investment behavior of important groups of real-world investors. The core methodology used in this research will be that of multidimensional scaling and several closely


related numerical techniques. These procedures, whose applications within financial literature have been virtually nonexistent to this point, are outlined later in this chapter and described in considerable detail in Chapters II and III.

Successful completion of this research will reveal whether normative portfolio selection models should be considered, at least for a first approximation, as being reasonably descriptive of the actual perceptual and behavioral investment patterns of important market participants. The goals of this research require at least tentative answers to the following questions:

1. How do investors perceive similarities or differences among potential investment alternatives?

2. What factors are used by investors to evaluate investment alternatives?

3. Can individual investment behavior be predicted from similarity and preference data of the kinds required by multidimensional scaling procedures?

4. Can individual perceptual and behavioral patterns be generalized over enough market participants to allow for the construction of larger-scale predictive models of investment behavior?

RATIONALE FOR THE STUDY

The would-be investor in common stock has at his fingertips a vast amount and variety of factual information, opinions, and recommendations which he might utilize in making investment decisions. Published internal data, brokerage house research reports, and investment advisory services allow an investor to evaluate the earnings and dividend history of the firm, past market price movements, growth rates of sales and assets, forecasts of future earnings and dividends, expected levels of price appreciation over time, assessments of the firm's management, and nearly any other variable which might influence the decision to invest. If all the information potentially available could be fully utilized by an investor, he would
presumably assess the relative position a security occupies along any and all of the preceding unidimensional attributes vis-a-vis the values exhibited by alternative choices, then make his buy or sell decision by maximizing his multidimensional utility function for common stocks.

Unfortunately, the human investor is generally incapable of assimilating and evaluating all the information available to him at a given time concerning even a relatively small group of stimuli. Even if masses of unrelated data are boiled down or grouped into several "summary" measures or variables, it has been shown that the human decision maker cannot, in general, make consistent or rational judgments on the basis of a large number of variables.

Partially for these reasons (but also largely because of ease of computation and exposition) normative portfolio models developed over the past two decades have consistently been limited to security and portfolio evaluation along only two dimensions, nearly always some variation of the Markowitz mean-variance approach. Whether such a severe restriction on the dimensionality of the investment decision process is necessary or appropriate, even considering human information processing limits, seems open to serious question. Furthermore, especially in empirical studies aimed at verifying various "market models," there has been a "tendency to presuppose knowledge of the dimensions of the area being investigated in

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5 Several articles have been published which explicitly detail some of the very real limitations on the human capacity to process information. See for instance D. B. Yntema and G. B. Mueser, "Remembering the Present State of a Number of Variables," *Journal of Experimental Psychology*, LX (1960), 18-22.

terms of (two) presumed unidimensional attributes, risk and return.7
Only in a relatively few laboratory studies have systematic attempts been
made to discern the salience of additional variables in the individual
investment decision process.8

It appears therefore, that the degree to which normative portfolio
selection models actually reflect the perceptual and behavioral patterns
of "real world" investors is as yet unknown. This research is designed
to "bridge the gap" between normative and descriptive models of investment
behavior by identifying and exposing the underlying structure of the fac-
tors involved in the investment decisions of individuals. The determi-
nation of the dimensionality and dimensions of the complex behavior known
as "investing" will be studied through the use of multidimensional scaling
and several related statistical tools. Once the dimensions or attributes
which influence individual investment behavior have been identified, the
usefulness of both the technique and the results of the research for the
construction of first individual, then larger-scale predictive models,
will be assessed.

Before discussing the hypotheses to be tested in this research, the
following section will introduce and briefly describe the experimental
technique known as multidimensional scaling.

WHAT IS MULTIDIMENSIONAL SCALING?

Multidimensional scaling is a technique which first originated in
the field of psychology over three decades ago. The major contributions

7Reza Moinpour, "An Empirical Investigation of Multidimensional
Scaling and Multidimensional Unfolding to Predict Brand Purchasing Be-
havior" (unpublished Ph.D. dissertation, The Ohio State University,
1970), p. 3.

8Clayton P. Alderfer and Harold Bierman, Jr., "Choices with Risk:
Beyond the Mean and Variance," Journal of Business, XXXIII (July, 1970),
341-353.
to the theory of multidimensional scaling have come mainly from the
science of psychometrics, which is concerned with measuring and quanti-
fying psychological variables. Nevertheless, in recent years the use
of the MDS technique has spread rapidly into a wide variety of academic
fields, including political science, biology, sociology, geography, and
the languages.

Recently, MDS has found application in several areas of marketing
research, including studies of consumer perception and brand awareness,
advertising effectiveness, market segmentation, and product life-cycles.
In fact, the most prominent contributor to the development of MDS theory
and application in recent years has been a student of market research,
Dr. Paul Green of The University of Pennsylvania. Few, if any, appli-
cations of the MDS technique have appeared in well-known financial
journals.

The essence of MDS is the attempt to represent a set of objects
(stimuli) as points in a geometric space of minimum dimensions, such
that the interpoint distances correspond to a subject's perception of
the degree of relationship (similarity, distance, or other measures of
proximity) between the objects themselves. In general, this means that
stimuli perceived to be quite similar by a respondent will be represented
by points quite close together in the final r-dimensional point configu-
ration, while a large distance between two points would indicate a
perceived lack of similarity between those two stimuli.

Figure 1 is an example of a two dimensional representation of re-
pondents' similarities judgments among a variety of potential investment
alternatives or outlets for investable funds. Responses for this appli-
cation of multidimensional scaling were gathered from students in an MBA-
level investment course at Ohio State University. The input data for
FIGURE 1

MDSCAL INVESTMENT CONFIGURATION
FROM O.S.U M.B.A. STUDY*

*Points are identified as follows:

1. Cash
2. U.S. Savings Bonds
3. Home
4. Life Insurance
5. Savings Account - Bank
6. Savings Account - S & L
7. Undeveloped Real Estate
8. Corporate Common Stock
9. Corporate Bonds
10. Corporate Preferred Stock
11. Municipal Bonds
this configuration consisted of the averaged degree of relative similarity perceived by subjects between all possible pairs of the eleven investments (fifty-five pairs in all). The MDS technique then found a geometric arrangement of the stimulus points (in the space of lowest dimensionality) in which the ranks of the interpoint distances corresponded closely to the subject's rankings of interstimulus similarity. Thus the maximum interpoint distance in the stimulus configuration should be between the pairs of stimuli judged to be least similar, and so on. It should be noted that quite often more-than-two dimensional spaces are needed to provide a point configuration which closely corresponds to all estimates of perceived similarities or psychological "distances" between stimuli.

At this point, it should be reemphasized that the only stimulus attribute which subjects are explicitly required to evaluate is relative "similarity" (or, as we will discuss later, "preference"). Nevertheless, the heart of the MDS technique is the assumption that the dimensions of the point configuration represent stimulus attributes which the respondent uses in making such similarity comparisons. This assertion leads, then, to the problem of conclusively "identifying" the axes (or the dimensions) of the resultant spatial representation of the stimuli. MDS methods do not automatically provide labels for the dimensions. Such labeling must be accomplished in a largely subjective manner, often with the use of measures of correlation between known or judged variable levels and the projections of stimulus points along the various axes of the final configuration.\(^9\)

\(^9\)In the case of Figure 1, the horizontal axis was hypothesized to represent expected return, while the vertical axis appeared to represent the degree of risk associated by the respondents with the various investment alternatives.
The potential usefulness of the MDS technique in revealing a subject's perceptions of a stimulus set should now be apparent. Rather than requiring a respondent to evaluate a given stimulus on a variety of unidimensional scales (a process which limits the responses to the variables conceived by the experimenter, and which requires the respondent to go through the unfamiliar process of explicitly separating the influence of one stimulus attribute from that of another) MDS asks only that the respondent compare the "similarity" of one object to another. No mention need be made of any of the stimulus characteristics or attributes (e.g., investment risk, marketability, return, etc.,) which the experimenter has hypothesized as influencing investor perception. The identification of those factors is left until later when a suitable geometric configuration has been found and when a statistical determination of the salient perceptual dimensions can be carried out.

If the MDS technique had only been developed to this point, to the representation of subjects' perceptions as points in a geometric space, it would still provide a useful tool in the development of models of individual perceptual behavior and allow a first approximation to be made of a model of individual differences in buying or preference patterns. Within recent years, however, a variation of the basic MDS tool has been developed based on work first reported by Coombs,\(^\text{10}\) and later by Bennett and Hays.\(^\text{11}\) These newer techniques (called "unfolding" methods from the original Coombian discussion) allow for the construction of a "joint"


space which combines the perceptual "similarities" information discussed above with additional attitudinal or "preference" data for the same stimuli.

If both similarities and preference data—or, in some models, preference data alone—is gathered, modern "unfolding" algorithms allow the determination of an individual's "ideal" point within the same metric space in which the stimulus configuration is located. This ideal point is assumed to represent a hypothetical stimulus possessing that unique combination of the underlying attributes which would be preferred above all other attribute combinations. Figure 2 shows a hypothetical distribution of several ideal points among the perceptual map of the "investment alternatives" stimuli discussed earlier. Each ideal point is generated from the preference data gathered from a single respondent. Thus, each subject can be represented on the stimulus map by a single point which represents that attribute combination which he would prefer above all others. The only assumption is, of course, that the single stimulus configuration shown in this diagram is an appropriate representation of the perceptual pattern of all individuals represented by an ideal point.

The usefulness of the development of the "ideal point" concept should now be clear. An individual's ideal point can be thought of as the combination of attributes resulting in maximum utility to a respondent. A reasonable assumption would be that utility declines monotonically and symmetrically with increasing distance from the ideal point.\(^{12}\) If this is the case, then stimuli lying near the ideal point would be perceived as having a high utility, while the perceived utility of other stimuli would

\(^{12}\)A variety of different utility models are available. Several will be discussed in later sections dealing with the construction of predictive models and the use of the PREF-MAP program.
FIGURE 2

LETTERED POINTS REPRESENT A HYPOTHETICAL DISTRIBUTION
OF INDIVIDUAL "IDEAL POINTS" AMONG THE
INVESTMENT CONFIGURATION OF FIGURE 1
decrease as their distance from the ideal point grows larger. In essence, the perceived utility of a given stimulus varies inversely with its distance from the ideal point. Figure 3 illustrates the assumed utility function and the resultant two-dimensional isopreference curves. These techniques form the foundation of the predictive models of investment behavior developed in subsequent sections of this research.

In summary, MDS and MDU (multidimensional unfolding) techniques provide the researcher with a set of tools to answer the following questions:

1. What is the dimensionality of perceived similarities and differences among a set of stimuli?

2. What are the salient attributes, characteristics, or dimensions used by respondents to differentiate or evaluate a group of stimuli?

3. How do individuals differ in their perceptions of and preferences for a given group of objects?

4. How can a valid model be developed to predict individual preference among a group of stimuli?

The way in which these questions relate to the central objectives of this research can be seen in the following section in which the specific hypotheses to be tested in this dissertation, as well as a brief discussion of the rationale underlying their formulation, are presented.

HYPOTHESES

H1: The configuration of the stimuli set will be represented by a space of low dimensionality (i.e., at most, three dimensions).

The justification for this hypothesis follows from the brief discussion earlier concerning human information processing capabilities, from the theory of portfolio selection which has gained wide acceptance in financial literature, and from the one previous application of MDS to the investment process.
FIGURE 3

ILLUSTRATIVE UTILITY FUNCTION AND ISOPREFERENCE CONTOURS

Utility Function of Person A

A: Illustrative Utility Function

"Ideal Point" of Person A

Decreasing Preference

E: Isopreference
Little more need be said about the psychological evidence which leads to the conclusion that individuals tend to "boil down" complex decision problems by concentrating on a relatively few stimulus attributes. Especially in the area of potential securities investments where alternatives are, for all practical purposes, infinite, the limiting of evaluation procedures and information requirements to a fairly small number of salient attributes would seem to be a prerequisite for arriving at any decision at all.

Nevertheless it is still unknown whether, as normative portfolio selection models suggest, investors should or actually do limit their decision criteria to only two attributes of the investment alternative being considered (in most models, expected risk and return). Several studies have suggested that higher-order moments of price distributions may be salient characteristics of investors' perceptions of and preferences for alternative investments.¹³ Sauvain advocates the evaluation of potential investments in terms of nearly a dozen different attributes, including several varieties of risk and a half-dozen "desirability of ownership" qualities.¹⁴ Although it seems unlikely that many individuals would follow such evaluative techniques to the letter, this approach suggests, at least, that two dimensions (no matter what their labels) may not entirely characterize the security selection process for a large number of investors.

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Green has utilized MDS techniques in a study of common stock perceptions and preferences of a group of Wharton MBA candidates. In that study, the author found that three dimensions, not two, were needed to yield configurations which accurately represented the perceptual judgments of respondents. Thus, it appears that to hypothesize an adequate representation of investors' perceptual behavior in only two dimensions would be giving too much weight to theoretical portfolio selection models found in financial literature; and not enough weight to the empirical observations, both formal and informal, which are available to us from "real world" experiences.

H2: Significant differences exist between the perceptual patterns of various groups of market participants. These perceptual differences between investor groups may arise because of differences in (a) the amount of information obtained, (b) the "investment context" in which decisions are made, and (c) the nature and degree of homogeneity among securities in the investment "universe" under consideration.

The first test under H2 will be concerned with determining the effects of increasing levels or amounts of information on the perceptual patterns of investors. For this purpose, two groups of security analysts will be questioned. One group will be comprised solely of analysts who "specialize" in the same industry or category of common stocks, such as "chemical analysts." The other group will be made up of "non-specialists," or security analysts whose interests or specialities lie in other categories of stocks. It will be assumed that the "specialists" will be considerably more familiar with, and will have obtained a great deal more information pertaining to the single industry stocks used as stimuli than the non-specialists. It should be revealing to determine in what way

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additional information which the "specialist" obtains modifies the perceptual configuration from that of the "naive" non-specialist.

At this point, it might be appropriate to forecast the manner in which the perceptual patterns of the two groups will be found to differ, based on certain assumptions about the information flows reaching both the "specialist" and the "non-specialist" investor. For the speciality analysts, it appears that (1) sources of information would be relatively similar for all group members, (2) interaction among group members would be high, and (3) more information than can be efficiently utilized in making investment decisions will be available to the analyst. These assumptions lead to the hypothesis that the perceptual patterns of speciality analysts will be characterized by (a) a high degree of homogeneity among analysts, and (b) a perceptual space of higher-than-average dimensionality, because of the limited number and type of security alternatives he must differentiate or classify.

On the other hand, if similarities judgments are gathered from a random group of individuals normally concerned with a different or far wider range of securities, it would appear that (a) a wide variety of sources and types of information would be used to formulate perceptions, and (b) little interaction, especially in relation to the single group of stocks used as stimuli, would have taken place between analysts. This situation would appear to lead to perceptual maps of somewhat lower dimensionality, and somewhat higher diversity than in the case discussed above.

In addition to differences in perception due to varying information levels, differences in perception might also arise due to changes in the "investment context," the "situation," the "point of view" from which an
individual evaluates investment alternatives. Of special interest in this case are the systematic differences, if any, which exist between the perceptual patterns and dimensions of the security analyst and those of the "portfolio manager." This gap between the "recommender" and the "decision-maker," between the "staff" officer and the "line" officer, was highlighted by Adam Smith in *The Money Game*:

> . . . there is a personality difference between the people who are good at finding stocks and people who call the shots on the timing and manage the whole portfolio. Security analysts dig down information and come up with an idea about what should be bought or sold, but they do not necessarily make good conductors for the whole orchestra. If they are woodwind players to start with, they tend to hear the whole orchestra as woodwinds, and it takes another type to keep the woodwinds and brass and strings in line.16

It is possible that the "personality differences" alluded to by Mr. Smith will be transformed into perceptual spaces for common stock stimuli based on a different number or type of investment attributes for security analysts as opposed to portfolio managers. By comparing the responses of these two groups of market participants to the same list of (chemical) stocks, we may begin to systematically isolate both the similarities and the differences in the ways in which these two important market groups perceive and evaluate common stock investments.

Finally, perceptual configurations for a single class of investors, portfolio managers, will be obtained for two different common stock sets; the chemical industry stocks mentioned above, and a diversified group of stocks selected without regard to industry. The purpose of this experiment is to observe the degree of generality of perceptual patterns across different stimulus sets. It seems likely that, in general, a higher number

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of dimensions would be required to portray accurately the pattern of relationships between a highly diverse set of stimuli than would be needed to represent the judged similarities among stocks of a single industry. The results of this experiment should shed further light on the advisability of and the requirements for the construction of generalized descriptive or predictive investment selection models.

H3: Significant "clusters" of individuals within the larger sample groups can be identified as having similar perceptual judgments or patterns in relation to the stimuli set, in a sense representing similar "points of view" in security evaluation.

Although stimulus configurations will be generated and studied for each individual security analyst or portfolio manager, an assessment of the generality of judgmental perceptions and preference patterns is necessary before the possibility of the formulation of larger-scale descriptive or predictive models can be considered. It is hypothesized that within the various investor groups, one or more "subgroups" will be identified as having sufficiently similar "points of view" concerning both the salient attributes which differentiate these stocks and the relative values of the stimuli in terms of these important variables that a single perceptual map could be said to adequately represent their combined judgments of the configuration of the stimulus set. Once such homogeneous "points of view" are identified, individual differences in preference patterns can be closely studied by superimposing the "ideal points" of relevant respondents directly onto the scalar configuration of stimulus points.

In this way, predictive models of the investment behavior of an entire group of investors could be built; first by summarizing the behavior of the individual "clusters" or subgroups of the individuals previously identified, then, depending on the number and "tightness" of the clusters, developing a "weighting" procedure for the individual cluster results.
which would generate a measure of relative "attractiveness" of a given security to the analyst group as a whole. An evaluation of the usefulness of such a model could be made by comparing the relative investment merit evaluations generated by such a model to actual analyst investment decisions. A further discussion of the exact form of the generalized security selection model to be tested in this research will be discussed in H₄ and in Chapter III, Methodology.

H₄: Assuming stimulus configurations are generated containing a minimum of two dimensions, both a "return" and a "risk" axis can be identified. The "labels" for any higher order axes will not be hypothesized at this time.

H₁ through H₃, discussed above, were concerned with discerning general patterns of individual and group investment behavior. Beyond this problem, however, lies the attempt to "label" the r-dimensional (hopefully, r = 3 or less) stimulus configurations by correlating projections of the points in the spatial map along each individual axis with stimuli values in terms of a variety of potential investment attributes which have been calculated outside the MDS framework. Thus, the proper "labeling" of the axes in the MDS technique depends largely on the skill of the researcher in identifying and measuring each stimulus in terms of possible dimensional attributes, then correlating these "outside" values with the order and position by which each stimulus is characterized along various axes of the perceptual space. The "outside" data can consist of both purely objective statistical measures and of perceptual impressions gathered from respondents of their "subjective" rankings of stimuli along a variety of common or potentially important unidimensional attribute scales.

To assume that either perceptual or objective (from ex post data) return and risk attributes will form two of the more salient perceptual dimensions seems a not unreasonable assumption. To deny this would seem to
assume that the entire foundation of portfolio selection theory for the past two decades was laid on a totally incorrect view of the individual investment process, and further that the development of the two-dimensional portfolio models has had no impact at all in the world except on the pages of financial journals. This viewpoint cannot be defended at this time.

It does appear possible, however, that by limiting portfolio selection models to considerations of only a risk variable and a return variable, the opportunity of constructing more accurate representations of the individual's investment behavior in models which include another dimension or two has been overlooked. Green, in the article discussed previously, labeled two of the perceptual dimensions of a group of MBA students "risk" and "return" in describing their impressions of a list of common stocks. In this effort, he used a combination of both objectively measured statistical data and outside respondents' subjective rankings of the stimuli in terms of several potentially important investment attributes. These rankings were then transformed to interval scales through the use of Thurstone scaling techniques. He reports being unable to label a third salient dimension found in the perceptual maps of the students. However, his "return" measure was more a measure of "growth" than "returns," and it seems possible that a knowledgeable application of various return, risk, and growth measures to the stimulus maps would have resulted in satisfactory (in a statistical sense) labels for all three dimensions.\footnote{Green and Maheshwari, "Common Stock Perceptions and Preference," p. 445.}

As a second objective within this area, an attempt will be made to obtain purely statistical labels for the axes, based entirely on ex post data which is widely available. In this effort, the objective will be to determine which of a wide variety of ex post statistical measures, especially
in the area of risk, is most closely correlated with the investor's perceptions of these same qualities. If good statistical "fits" are found between the stimulus positions along various axes of the perceptual map, and their ranks in terms of ex post measures of risk, return, growth, profitability, etc., then an important first step will have been taken toward (1) eliminating the controversies surrounding the question of which statistical measures are "best," and (2) making possible the construction of portfolio selection models, based entirely on ex post statistical data, which would satisfactorily describe individual or group investment behavior. More will be said about the construction of predictive models in a later section.

H₅: An inverse relationship exists between stimulus-ideal point distances in an individual or group "joint space" and the degree of preference for a given security exhibited by individuals or groups in the construction of hypothetical portfolios. For individuals, this implies that the mean stimulus-ideal point distances for those stimuli selected for inclusion in hypothetical portfolios will be less than the comparable distances for the stocks not included. For groups, this hypothesis implies that the ranking of the stocks according to their proximity to the group "ideal point" will correspond to the ranks of their frequency of inclusion in group members' ideal portfolios. The distance measure can be stated as:

\[ d_{ij} = \sqrt{\sum_{k=1}^{r} (X_{ki} - X_{kj})^2} \]

Where:  
\( d_{ij} \) = Euclidean distance between stock \( j \) and ideal point \( i \) in a space of \( r \) dimensions  
\( X_{ki} \) = the \( k^{th} \) coordinate of the individual's "ideal" point  
\( X_{kj} \) = the \( k^{th} \) coordinate of the \( j^{th} \) stimulus point

\( H₅ \) is the beginning of the effort to construct a predictive model of the investment behavior of both an individual and of a group of individuals.
As mentioned earlier, "ideal points" are hypothetical stimuli whose positions in the space are "derived from the subject's preference ratings over individual stocks. They are interpreted as possessing that combination of perceived attributes which would be most highly preferred by each subject." When both the "ideal point" and the stimulus points are located or plotted in the same r-dimensional space, then, if it is assumed that utility is monotonically decreasing as distance from the "ideal point" increases, it should be possible to predict which securities would have the greatest likelihood of being selected for inclusion in an investor's portfolio. (See Figure 4). In this way, by comparing predicted preferences with securities chosen for inclusion in an individual's hypothetical optimum portfolio, it will be possible to assess the ability of MDS techniques to construct accurate predictive models of stock selection.

Furthermore, it may be possible to utilize the "clusters" of analysts identified in $W_4$ to begin the construction of larger-scale predictive models of investor behavior. The identification of investor groups with homogeneous perceptions of and preferences for common stock stimuli would obviously aid in the extension of predictive results from individuals to large and significant groups of market participants.

It must be realized, however, that the identification of clusters of investors with similar perceptual viewpoints does not rule out the possibility that wide differences in preference for various common stocks will be revealed by the subjects of this research. Such a situation would be indicated by a wide dispersion of individual "ideal points" within the common perceptual space representing that cluster of individuals. From this evidence a preliminary judgment about the consistency or generality

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18 Ibid, p. 452.
FIGURE 4

HYPOTHETICAL STIMULUS-Ideal Point Distance Calculations

Based on the relative proximities of individual "ideal points" (A, B, and C) and security stimuli (1, 2, and 3), the following preference rank orders could be hypothesized for each individual analyst:

<table>
<thead>
<tr>
<th>Analyst</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Most Preferred</td>
<td>Security 3</td>
<td>Security 1</td>
<td>Security 2</td>
</tr>
<tr>
<td>Second Most Preferred</td>
<td>Security 1</td>
<td>Security 2</td>
<td>Security 3</td>
</tr>
<tr>
<td>Least Preferred</td>
<td>Security 2</td>
<td>Security 3</td>
<td>Security 1</td>
</tr>
</tbody>
</table>
of preferences even among investors with similar points of view can be
made. If such a wide divergence in preference patterns is found among
cluster members then, in order to arrive at a predictive investment selec-
tion model for the cluster as a whole, a procedure which weights or
aggregates individual preferences into an overall cluster preference
ranking will be used and tested against exhibited investment behavior.

Finally, if no tight clusters or broad-based points of view are re-
vealed within various analyst or portfolio manager groups, then the
predicted investment behavior of full groups of these individuals will be
constructed by directly aggregating or combining the individual predicted
investment preferences into group preference measures.

The preceding discussion has introduced the technique of multi-di-
ensional scaling and defined the hypotheses to be tested in this research.
In addition the rationale and, in some cases, previous empirical results
in related areas of research which underlie these hypotheses have been
noted. Chapter II will survey existing MDS literature, focusing both on
articles of a conceptual nature and those which illustrate specific ap-
plications of this and related scaling techniques.
CHAPTER II
REVIEW OF THE LITERATURE

The techniques of multidimensional analysis used today by researchers in many fields were largely developed within the area of statistical psychology, of psychometrics. For this reason, most of the literature on multidimensional scaling, especially those articles dealing with the conceptualization and development of the technique itself, is found in psychological journals. Only within the past three to four years have business researchers (primarily within the area of marketing) begun to utilize multidimensional scaling in their work and to publish articles in business journals which extend the methodology itself or illustrate useful applications of the technique in business-oriented research projects.

The existing literature in this area could be classified in several ways. One approach would be to categorize available writings under one of three headings: Multidimensional Scaling (MDS), Multidimensional Unfolding (MDU), and Models of Individual Differences.

For the purpose of this paper, however, relevant literature will be classified as being either developmental in nature or applicational in character. Important literature related to the development of the theory and methodology of the field as it exists today will be subdivided into writings concerning (a) multidimensional scaling techniques, (b) the development of multidimensional "unfolding" as a scaling methodology, and (c) the construction of "individual difference" models and identifying algorithms. Literature highlighting important or illustrative applications

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of MDS techniques will be divided into those articles originating from (a) nonbusiness (primarily psychological) disciplines, and (b) those applications of MDS methods to business research (found almost entirely in marketing literature) which have been reported.

Computer routines and programs that have been developed to facilitate the application of MDS techniques will not be discussed under a separate heading. These contributions will instead be fitted into the above taxonomy where appropriate by noting both the developers and the functions of special computer programs which provide solutions to specific scaling problems.

I: CONCEPTUAL AND METHODOLOGICAL DEVELOPMENT

A: Multidimensional Scaling

The impetus for the development of multidimensional techniques of scaling and measurement was given by Richardson who argued that psychological judgments are based on a complex of variables, and who recommended "the extension of psychophysical methods to more than one dimension."

He illustrated a possible approach to the multidimensional scaling problem by obtaining experimental data on subject's perceptions of the relative similarities of Munsell colored cards, then scaling these similarity judgments with the use of Thurstone's paired comparison method to obtain a metric measure of "psychological distance" between the stimuli. These results were then submitted to a model developed by Young and Householder which found a configuration in n-dimensional space whose interpoint distances

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most closely matched the perceived inter-stimulus distances derived from the Thurstone scaling procedure noted above.  

Attneave, while criticizing the assumption of Richardson and others that psychological space is Euclidean in nature (he suggested the use of the "city-block" metric which measures the distance between stimuli as the arithmetic sum of the differences of their projections on each dimension), also provided a concise statement of the objectives of multidimensional psychological scaling. He wrote:

A comprehensive understanding of psychological similarity should enable us to describe quantitatively the factors determining judgments of similarity, and it should involve a knowledge of the measurements which we need to make of physical stimuli in order to predict the psychological similarity which they will manifest in various situations.

The earliest MDS models (such as that developed by Young and Householder) could only use input data in the form of ratio scaled distances between stimuli to produce an n-dimensional configuration in which inter-point distances were ratio scaled and matched as closely as possible to the input distances. Thus, these early models are termed "fully metric," to indicate both the requirements of the input data and the results of the scaling procedure. Unfortunately, in many perceptual experiments, subjects cannot be assumed to report ratio scaled distances between stimuli, but rather only comparative or ranked estimates of relative similarity or difference among stimulus pairs. For this reason, considerable effort was made by early scaling theorists to develop techniques to convert

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"comparative" distance perceptions (i.e., rank-order data) to "absolute" distance measures.

Torgerson was the first to propose an "additive constant" technique for transforming rank-order data into interval-scaled distance measures. At the same time, he improved the earlier Young and Householder algorithms to allow more flexibility in the handling of incomplete or fallible data. In a subsequent paper Messick reviewed the development of MDS techniques to that point and discussed a variety of experimental techniques (paired comparison approaches, methods of diads, triads, tetrads, etc.) for obtaining relative and absolute interstimulus distances.

Several early papers by Shepard related the concept of stimulus "generalization" (i.e., the probability that a given stimulus will be "confused" with another) to the concept of psychological "distance" between the stimuli. In his first paper, Shepard introduced a procedure for developing relative inter-stimulus distances from "confusions" data. In his first 1958 article, he showed how stimuli could be positioned in a


multidimensional space solely on the basis of the relative frequency with which one stimulus was mistakenly taken for another. Finally, in a second 1958 article, he attempted to determine "the form of the function relating generalized response-tendency to inter-stimulus dissimilarity." Such a derivation requires an agreed-upon measure of "dissimilarity," which Shepard defined to be "the distance between points in a psychological space." Thus, in these three studies Shepard laid the psychological construct of "inter-stimulus distance" on solid theoretical ground.

Torgerson's book serves both as a summary and as a capstone to the development of fully metric multidimensional scaling models. Torgerson described the two separate and distinct stages or operations of the fully metric MDS models, as first, the determination of the distance function which transforms rank-order data into the ratio-scaled inter-stimulus distance measures required by the fully metric scaling models then available, and second, the identification of the spatial model of the stimuli in the lowest dimensionality in which interpoint distances closely match the calculated inter-stimulus distances of the previous stage. Torgerson also proposed a statistical measure of "goodness of fit" in which derived interpoint distances between stimuli were compared to observed data.

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11 Ibid., p. 244.

As noted previously, the assumptions underlying the use of fully metric scaling techniques (i.e., that respondents could provide ratio scaled inter-stimulus perceptual judgments, or that the determination of the proper "distance function" could transform ranked data into ratio scaled measures of perceptual similarity) were rather severe, and appeared to be holding back the acceptance and use of MDS methods in many areas of psychological measurement. It remained for Shepard and the widespread availability of high-speed computers to provide the required mathematical techniques and data processing ability to develop non-metric multidimensional scaling; i.e., the ability to use rank-order input data to provide metric solutions.\textsuperscript{13} The Shepard MDS algorithm, which assumes only that the actual "psychological distance" between stimuli is a monotonic function of the perceived inter-stimulus proximity measures, has the following objectives:

(a) to array stimulus points in an n-dimensional space such that interpoint distances in this space are monotonically related to the initially given proximity judgments,

(b) to determine the minimum number of spatial dimensions required to achieve interpoint monotonicity with input data, and

(c) to plot the true shape of the initially unknown "distance function" relating proximity to distance.\textsuperscript{14}

Shepard also pointed out that a measure of the degree of "non-monotonicity" of a given configuration can provide an indicator for determining the proper minimum dimensionality for accurate mapping of a given set of stimuli.\textsuperscript{15} In a second 1962 article, Shepard showed how his


\textsuperscript{14} \textit{Ibid.}

\textsuperscript{15} \textit{Ibid.}
non-metric algorithm could reduce the number of dimensions required to portray stimuli previously scaled by fully metric techniques in earlier scaling articles by other writers. Finally, in order to demonstrate the strength of his non-metric algorithm, Shepard performed a series of simulation experiments in which known configurations were compared with the results of applying his non-metric MDS technique to rank-order input data. He showed that with as few as eight points, the minimum correlation between the interpoint distances resulting from the application of his algorithm to simple rank-order data and the interpoint distances of a known two-dimensional configuration was .99. For higher numbers of stimuli (points) the two configurations were virtually indistinguishable.

Although the Shepard papers noted above were milestones in the development of non-metric MDS methods, extensions and improvements in his basic algorithms soon appeared. Of special note is a paper by Kruskal in which the "monotonicity" requirement assumed central importance. He developed a technique which essentially performs a monotone regression of distance on dissimilarity for a given configuration. This "statistical fitting" procedure provided a convenient measure for the goodness of fit between a given scaling configuration and the input data. Thus, the residual variance of the regression operation enters into the calculation of Kruskal's "stress" measure, defined as:


Stress = \( S = \left[ \frac{\sum_{i,j} d_{ij} \left( d_{ij} - \hat{d}_{ij} \right)^2}{\sum_{i,j} d_{ij}^2} \right]^{1/2} \)

where \( d_{ij} \) is the distance from point \( i \) to point \( j \).

If point \( i \) has orthogonal coordinates \( (X_{i1}, X_{i2}, \ldots, X_{ir}) \) then we have:

\[
d_{ij} = \left[ \sum_{s=1}^{r} (X_{is} - X_{js})^2 \right]^{1/2}
\]

The \( \hat{d}_{ij} \) are a monotone sequence of numbers which minimize \( S \). 18

In a subsequent paper Kruskal detailed both a numerical procedure and a computer program to perform his scaling technique. 19 Because of their fundamental nature and methodological similarities, the combined works of Shepard and Kruskal are often denoted as the Shepard-Kruskal algorithms.

Subsequent articles of methodological importance in the MDS area have been in the nature of increasing the flexibility or versatility of the basic Shepard-Kruskal algorithms, or in developing additional data manipulation techniques which can supplement the initial scaling results of an experiment. Miller, Shepard, and Chang devised an analytical approach using linear correlation techniques to provide a systematic

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"labeling" of the dimensions of a final stimulus configuration. Later, Carroll and Chang extended this form of analysis by allowing the calculation of non-linear correlations between outside "property" vectors and configuration dimensions. Cliff reported procedures for rotating factor solutions orthogonally until similar positions are reached, or for rotating a single factor solution orthogonally to reach a specified target matrix. Both these techniques have been utilized to aid in the comparison of scaling configurations between different subject groups. McGe introduced the concept of elasticity in the monotonic "distance function" relating distance to dissimilarity, a notion which previewed later approaches to the consideration of individual differences in perception.

In another article Ramsay criticized several approaches to the collection of perceived similarity data and offered suggestions for their improvement.

Two recent simulation studies of common non-metric MDS techniques have been reported. Klahr applied simulation techniques in an effort to determine the degree of significance for various levels of Kruskal's stress measure as a function of the number of stimuli scaled and the

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22 Norman Cliff, "Orthogonal Rotation to Congruence," Psychometrika, XXXI (March, 1966), 33-42.


dimensionality of the final configuration. He concluded that with ten or more stimuli, the chances of achieving satisfactory stress levels in spaces of low dimensionality from purely random data are very low.\textsuperscript{25} In essence, his study provided statistical "bench marks" for the determination of acceptable stress levels for scaling configurations of \( n \) points in \( r \) dimensions. In a similar study Young studied the degree to which a known configuration was reproduced by common non-metric algorithms as a function of (a) the amount of error in the data, (b) the number of stimuli, and (c) the dimensionality of the underlying real configuration. His most significant conclusion was that if the ratio of points to dimensions is high, accurate metric information is recovered even if the data contain large amounts of error.\textsuperscript{26}

The development and increased use of MDS techniques during the last decade has been spurred by continued modification and improvement of the basic non-metric MDS computer programs. Guttman and Lingoes offered their own computerized non-metric scaling procedure soon after the earliest Shepard-Kruskal techniques were published,\textsuperscript{27} while Young and Torgerson reported the development of TORSCA, their own computer version of the Shepard-Kruskal analysis.\textsuperscript{28} Also of importance was the development of a


\textsuperscript{26}Forrest W. Young, "Nonmetric Multidimensional Scaling: Recovery of Metric Information," \textit{Psychometrika}, XXXV (December, 1970), 455-75.


program for orthogonal rotation and fitting, based on Cliff's early work, by Pennell and Young. Most recently, Young, in the development of TORSCA-9, and Kruskal, with MDSCAL-4M, have provided the researcher with fully integrated MDS programs which are flexible in terms of data inputs and versatile in terms of the output information and options available to the user.

B: Multidimensional Unfolding (MDU)

In parallel to the early development of the "fully metric" scaling models described in the previous section, researchers at this time were also formulating and using what are termed "fully non-metric" scaling techniques. The objective of the fully non-metric scaling models was to use non-metric input data (rankings or orderings of the stimuli, from several respondents, usually on the basis of "preference") to produce a rank order of stimulus points along salient perceptual dimensions. This process was termed "unfolding" (for reasons to be discussed shortly). Ultimately, the unfolding process was extended to allow the construction of a metric stimulus configuration similar to those arising from Shepard-Kruskal scaling of similarities data as discussed earlier. The major difference, however, between multidimensional scaling and multidimensional unfolding lies in the fact that the "unfolding" of preference data results in a "joint space" of both stimulus points and individual "ideal points."


Three facts should be emphasized at the outset of any discussion of unfolding algorithms or models based only on preference data. First, the pure unfolding algorithms require several sets of preference data in order to be used to construct the stimulus configuration and locate ideal points within the space. While MDS programs can construct a stimulus configuration from a single individual's similarity judgments between all pairs of the stimuli, MDU programs cannot achieve the same result from one person's preference ranking taken in isolation.

Second, MDU algorithms require not only multiple preference rankings, but also diversity of opinion as to the relative merits of each stimulus. In other words, if all individuals in a group report exactly the same preference ordering, the MDU algorithms are helpless in determining a stimulus configuration or the location of ideal points.

Thirdly, since unfolding algorithms produce only a single "joint space" containing a single stimulus configuration interspersed with individual ideal points, these models implicitly assume homogeneity of perception among the individuals whose preferences are obtained. In other words, the same set of dimensions are assumed to underlie individual perceptions of the stimuli, while differences in preference rankings are accounted for entirely on the basis of differing ideal point locations. With these distinctions between unfolding models and MDS techniques in mind, the following discussion will detail the development of scaling models which rely primarily on preference data to develop a joint space of stimulus points and "ideal" points.

The unfolding approach was first conceptualized and developed in a unidimensional form by Coombs. In his work he postulated the existence of a unidimensional continuum---a "J-scale"---along which both stimuli
and individuals can be positioned. The (initially unknown) scale value of a subject is his ideal point, and Coombs assumed that the relative preference of a subject for a given stimulus is determined by the relative subject-stimulus distance along the J-scale. Of greater importance, however, was his demonstration that an individual's rank order of preference for the various stimuli—the "I-scale"—could be viewed as the result of simply "folding" the J-scale at the individual's ideal point. In order to understand the attribute continuum underlying preference, therefore, it is necessary to "unfold" the rank order preference data to recover the underlying J-scale of stimulus and ideal points.

The Coombsian unfolding model was generalized to the multidimensional case by Bennett and Hays, who replaced Coombs' one dimensional J-scale with a multidimensional attribute space. Their approach takes preference rankings of several individuals and constructs a single joint space which contains both stimulus points and ideal points. In line with the previous discussion, however, the authors state that a major weakness of their unfolding model lies in the assumption that "subjects differ fundamentally in their preferences for the items, though they all view these items substantially the same within some common system of attributes." Although the work of Bennett and Hays produced an important generalization of the unfolding technique, it was recognized that their model

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might not be satisfactory for determining scaling solutions of high dimensionality or of large numbers of stimuli. Coombs, in an effort to overcome these limitations, proposed a metric version of his unfolding technique. He utilized a "median individual" as a central or average subject which represented a configuration of individuals containing the attribute space which generated their preference judgments. 35

In a related technique, Coombs and Kao showed how multiple factor analysis of the correlation matrix of individuals' ranked preference data would result in a space of dimensionality one greater than that obtained from an unfolding approach. 36 Ross and Cliff extended the above study and demonstrated that factor analysis could be used to recover the configuration (of objects and individuals) in the same dimensionality as the unfolding procedure if squared distances rather than direct distance measures between stimuli and individuals are correlated. 37

All of the unfolding models discussed to this point rely on preference data for a group of individuals to arrive at a single common stimulus configuration, presumably appropriate for all group members, among which are scattered individual ideal points. It is apparent that this approach—termed "internal analysis" by Carroll 38—precludes an analysis of important variations in the perceptual structures of individual group members.


To combat this difficulty, Carroll and Chang developed a procedure--termed "external analysis"\(^{39}\)--which relates the preference data of individual subjects to an "a priori" stimulus configuration presumably developed from a multidimensional scaling of that subject's similarity judgments. Several unique features of their model and mapping algorithm increase the flexibility and versatility of the unfolding concept in arriving at individual ideal points and utility functions. First, as mentioned above, the rigid assumption of a common perceptual space for all individuals was relaxed. This allows the construction of a unique joint space for each individual if desired.

Second, the Carroll-Chang model allows the construction of joint spaces on the basis of not one, but a hierarchy of four different utility models relating distance to preference. These varying utility models, termed "Phases" by the authors, differ in the ways in which individuals are assumed to stretch or rotate the perceptual axes of a given stimulus configuration in determining a preference ranking for the various stimuli. Phase I of their program provides the greatest degree of flexibility, allowing differential rotation and weighting (including negative weights) of the dimensions of a common perceptual space. Phase II simply allows differential weighting of configuration axes. Phase III constrains axis weights to be equal while assuming that preference ratings are related to the square of distances between stimulus points and the ideal point. Thus, this utility model most nearly approximates the results of the simple Coombsian unfolding procedures. Finally, Phase IV assumes a

vector utility model in which relative preference is assumed to be defined by the projections of stimulus points on a vector located in the configuration space. This form of utility model was initially proposed by Tucker.40

Carroll and Chang have termed the relating of preference data to a predetermined stimulus configuration "external analysis," and have designed the PREF-MAP computer program to perform the necessary calculations. This procedure and the nature of the results arising from the use of this program will be described in considerably more detail in later sections since an analysis of this nature forms a major part of the methodology of this study.

C: Analysis of Individual Differences in Perception

There is little doubt that significant differences in the dimensionality and dimensions of perception of a given stimulus group exist, especially among non-homogeneous groups of respondents. A variety of models have been designed to allow the experimenter to pursue a middle course between (a) constructing and analyzing a unique stimulus configuration for each individual, and (b) developing a single configuration for the entire group by aggregating or averaging data gathered from many respondents. The "individual difference" models discussed below were designed to allow the efficient identification of the degree and nature of differences in perception which exist among members of the respondent group.

A model developed by Tucker and Messick, called "points of view analysis" \(^{41}\) was the first attempt to explicitly identify individual differences in perceptual judgments. Their procedure involves the construction of a "subject space" by factor analyzing measures of correlation between the similarity judgments of different respondents. The objective is then to isolate (either subjectively or by using mechanical clustering techniques) homogeneous "clusters" or groups of subjects within the subject space. A subject group identified in this manner is presumed to exhibit a high degree of homogeneity in their perceptions of the stimulus objects. Thus, the similarity judgments for all cluster members can be averaged, or the similarity judgments for the individual closest to the centroid of the cluster can be scaled. In either case, the single stimulus configuration which results can be assumed to represent accurately the "point of view" of all the respondents within that single cluster of individuals. Comparisons may then be made, of course, across clusters and not among all possible pairs of individuals.

Although the Tucker-Messick "points of view" analysis is probably the most widely used technique for observing individual differences in perception, several criticisms of their model have been raised. Ross attacked the Tucker-Messick model primarily on technical grounds, arguing a lack of justification for the required factor analyzing of subjects based on perceived interpoint distances and concluding that "the solution we accept is merely a fiction accepted because of its convenience in data reduction." \(^{42}\) Cliff responded in defense of Tucker-Messick by arguing

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that Ross misinterpreted the objectives of "points of view" analysis and offering his own, less ambitious interpretation of the results of the Tucker-Messick model.\footnote{Norman Cliff, "The 'Idealized Individual' Interpretation of Individual Differences in Multidimensional Scaling," \textit{Psychometrika}, XXXIII (June, 1968), 225-32.}

More recently Tucker-Messick has been criticized on more conceptual grounds. Green and Morris noted that the "points of view" analysis makes no attempt to explicitly relate the stimulus configurations generated by one cluster of subjects with that of another. In other words, no systematic procedure is included in the model for the determination of the relative degree of similarity between the scaling results of different clusters. There is no attempt to determine whether different groups may have one or more dimensions in common.\footnote{Paul E. Green and Thomas W. Morris, "Individual Differences in Multidimensional Scaling," (paper presented at the Consumer Behavior Workshop of the American Marketing Association, Columbus, Ohio, August, 1969).} This argument was extended by Carroll and Chang:

\begin{quote}
It would be very surprising if the various configurations had no structure in common. Rather, one might expect that for example, one or two dimensions are the same in two different configurations while a third is different, or that the same dimensions are present, but they have different relative "saliences," of importances, for different people.\footnote{J. Douglas Carroll and Jih-Jie Chang, "Analysis of Individual Differences in Multidimensional Scaling Via an N-Way Generalization of 'Eckart-Young' Decomposition," \textit{Psychometrika}, XXXV (September, 1970), 283-319.}
\end{quote}

The apparent weaknesses of the Tucker-Messick approach to individual differences led others to formulate their own models or procedures for systematically identifying differences in perception. Johnson demonstrated how his hierarchical clustering model could be used to cluster individuals...
based on a measure of the similarity of perceived inter-stimulus distances among respondents.\textsuperscript{46} Also, McGee suggested dealing with individual differences by allowing each subject a unique monotone function relating distances to similarity judgments.\textsuperscript{47} Such a procedure is provided for in the MDSCAL program by Kruskal.\textsuperscript{48}

Although the above models found limited application, they still did not address themselves specifically to the problem of determining the degree of communality among the perceptual dimensions of different "clusters" of respondents. Recently, however, in work reported by Carroll and Chang, this problem appears to have been solved. The following discussion will be centered on the procedures developed and reported by Carroll and Chang, since the computer programs developed from their work are the ones which will be utilized in this research.

The Carroll-Chang individual difference model assumes that a single (common) perceptual space is appropriate for all respondents, but that each subject "weights" the dimensions of the common space uniquely.\textsuperscript{49} The input for the Carroll-Chang "shared-space" model consists of the inter-stimulus similarity judgments gathered from all respondents. The output consists of a single (group) stimulus configuration, plus a matrix of weights which indicate the salience or importance each individual attaches to each dimension in making his similarity judgments. Clustering of

\textsuperscript{46}Stephen C. Johnson, "Hierarchical Clustering Routines," Psychometrika, XXXII (September, 1967), 241-54.


\textsuperscript{48}J. B. Kruskal, "How to Use MD-SCAL," p. 5.

\textsuperscript{49}J. D. Carroll and J. J. Chang, "Analysis of Individual Differences."
individuals into groups representing homogeneous points of view can then be performed by examining the degree of correspondence across subjects in the weights or importances they attach to dimensions of the common perceptual space. The possibility of separate clusters having only a few, or even no dimensions in common is handled by allowing weights to be zero. Finally, a goodness of fit measure is obtained for the correspondence between subject similarity judgments and the stimulus configuration obtained when that individual's unique "weights" are applied to the dimensions of the "group" configuration.

As noted earlier, Carroll and Chang have developed a computer program, called INDSCAL, which performs the analysis described above. This program will be used and described more fully in subsequent chapters of this work.50

II: APPLICATIONS OF MDS TECHNIQUES

By far the majority of empirical applications of multidimensional scaling models have come from the field of psychology, where MDS techniques were originally developed. Although other disciplines evince a smattering of MDS applications, in recent years only the science of marketing research has utilized this experimental tool to an extent comparable to that of psychology. The following selection of MDS applications will, therefore, be divided into two broad categories; those originating in psychology or related disciplines, and those originating in the study of business (primarily in the field of market research). Within the psychological literature existing articles will be classified as being primarily either scaling applications or analyses of individual differences. The

50 Ibid.
business-oriented literature will be divided along different lines into
two classes, those articles produced by Paul Green and his associates,
and those applications described by other business authors.
A: Applications in Psychology
   1. Scaling Applications

The earliest applications of multidimensional scaling models uti-
лизed the fully metric algorithms originally developed by Young and
Householder. 51 Klingberg reported an early application of this technique
in examining the structure of relationships or associations among nations.
By scaling political science students' judgments of the degree of friend-
liness between various pairs of large countries, Klingberg constructed a
multidimensional configuration in which inter-point distances closely
matched the "psychological distances" derived from the input data. He
summarized the theoretical justification for utilizing spatial scaling
models to represent perceived relationships by saying:

   The smallest number of dimensions necessary to construct
   the points, with all mutual distances correct, should be
   the smallest number of factors necessary to explain the
   configuration, and it should be possible to give these
   factors (or dimensions) meaningful names. 52

The "meaningful names" Klingberg applied to the axes of his configu-
ration of nations were "degree of dynamism," "degree of communism," and
"degree of belligerency." 53

Subsequent studies often involved both extensions and applications
of the "fully metric" scaling models. Improved techniques of solving for

51 Young and Householder, "Discussions of a Set of Points."
52 Frank L. Klingberg, "Studies in Measurement of the Relations Among
   Sovereign States," Psychometrika, VI (December, 1941), 335-51.
53 Ibid., p. 345.
the "additive constant" were reported in studies of the scaling of psychological "attitudes" by Abelson, and an effort to examine the dimensionality of perceived attitude relationships by Messick. An article by Jackson, Messick, and Solley investigated "the appropriateness of MDS for structuring the perception of personality." They concluded that even such a complex construct as perceived personality could be scaled, and hence interpreted, on the basis of four dimensions or attributes of the stimulus subject. Attempts were made to provide "labels" for each of the four dimensions of the configuration.

Although the previously described applications of MDS procedures have generally involved the scaling of nonphysical stimuli (i.e., "attitudes," "personality," "nations"), several articles have attempted to scale subjects' perceptions of the relative similarity or difference between physical stimuli or objects. If these stimuli are allowed to vary in a systematic manner across a small number of attributes, multidimensional scaling solutions can provide clues to the nature of the perceptual processes in individuals.

Indow and Uchizono studied the perceptual maps of individual's perceptions of the similarity between various Munsell colors which were allowed to vary systematically in two dimensions, hue and chroma. They


57 Ibid., p. 315.
found that it was possible to represent perceived differences among
colors in a two-dimensional Euclidean space. The same Euclidean re-
results in three-dimensions were reported by Indow and Kanazawa when the
colors used as stimuli were allowed to vary over three dimensions: hue, chroma, and value. In both cases, configuration dimensions were di-
rectly related to the varying attribute dimensions. A later study by
Abelson and Sermat employed pictures of facial expressions as stimuli
in order to isolate, from the configuration and the dimensionality of
the scaling solution, what factors enter into the perceptions of emotion
embodied in a facial expression. In a more recent article Skager,
Schultz, and Klein applied the new non-metric MDS algorithms to scale the
similarities judgments of a set of artistic drawings. The authors postu-
lated relationships between characteristics of the drawings themselves
and characteristics of the individuals who perceived the drawings in
various ways and who expressed a preference for one or more of the
stimuli.

Returning to the scaling of more abstract stimuli, Boyd and Jackson
performed an analysis, conceptually similar to that of Skager, Schultz,
and Klein discussed above, in which the authors attempted to "study the

58 Tarow Indow and Tsukiko Uchizono, "Multidimensional Mapping of
Munsell Colors Varying in Hue and Chroma," Journal of Experimental

59 Tarow Indow and Kei Kanazawa, "Multidimensional Mapping of
Munsell Colors Varying in Hue, Chroma, and Value," Journal of Experi-
mental Psychology, LIX (May, 1960), 330-36.

60 Robert P. Abelson and Vello Sermat, "Multidimensional Scaling of
Facial Expressions," Journal of Experimental Psychology, LXII (June,
1962), 545-54.

61 Rodney W. Skager, Charles G. Schultz, and Stephen P. Klein, "The
Multidimensional Scaling of a Set of Artistic Drawings," Multivariate
role of personality in attitude development" by scaling both attitude statements and personality descriptions within the same spatial structure. A further application of MDS to determine the structure or determinants of personality impressions were reported by Rosenberg, Nelson, and Vivekananda.

The versatility of the MDS procedure was demonstrated by Brown and Schultz and Siegel, in articles designed to show how MDS could be used to design more efficient training programs or more appropriate performance evaluation procedures for a variety of job situations. In another interesting application of the MDS technique Brown and Brumaghim compared the extent to which scaling configurations based on "tactual" similarities judgments (i.e., how much objects "feel" alike) would conform to visual judgments (the extent to which objects "look" alike). The authors reported finding similar configurations across the two perceptual modalities.


Behrman and Brown report using both metric and non-metric MDS procedures to analyze visual perceptions of geometric shapes. A similar study by Berlyne, Ogilvie, and Parham utilized MDS techniques to study judgments of complexity, interestingness, and pleasingness of visual stimuli.

Finally, Anderson applied MDS techniques to the study of the dimensions or factors used by subjects to evaluate the similarity between various adjective pairs in common semantic differential testing situations. A central objective of his work was to compare the scaling configuration resulting from aggregating perceptual data over all subjects with individual subject stimulus configurations. He concludes that while "the aggregate stress figures consistently indicated a far better fit than did the corresponding individual stress values," the aggregate configuration "did not differ significantly from the configuration of most individuals."

2. Individual Difference Applications

A few studies in the area of psychological research have attempted to utilize MDS-related methods to assess the degree of similarity or differences in perceptions between groups of individuals, or to determine the degree of perceptual homogeneity among individuals of a single group. Several of the earlier papers in this area used relatively ad hoc

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procedures to identify differences in perception, while a few of the later papers utilized various individual differences models which were, by then, available and which were developed specifically for the purpose of identifying perceptual similarities or differences.

An early paper by Messick compared attitudes toward war, capital punishment, and treatment of criminals of a group of seminary students with those of a group of Air Force Officers. His comparisons of the stimulus configurations constructed from responses from each group resulted in his concluding that no significant differences in attitudes between the respondent groups could be substantiated. In a later article along these same lines, Messick compared judgments of "similarity of political thinking" among a group of twenty American politicians. The responses concerning the degree of similarity of political thought were gathered from two groups which differed in political affiliation; one group was Democratic, the other Republican. His results indicated little difference in the perceptual patterns of the two groups with different political affiliation, even though a Republican-Democratic axis was identified in the stimulus configuration as being an important factor in the judged similarity of political thought. Another study reached a similar conclusion concerning perceptual homogeneity in attitude data gathered from members of conservative and socialist political groups.


To this point, the analysis of differences in perception was carried out in a highly subjective, ad hoc manner. The development of the Tucker-Messick "points of view" model in 1963, however, introduced some order into individual difference research. A rudimentary form of their model was first applied by Helm and Tucker to illustrate differences in color perception.\(^\text{73}\) A more refined application of the Tucker-Messick model appeared in an article by Silver, Landis, and Messick, which used geometric shapes to "determine if there exists distinct sub-populations that make use of essentially different dimensions in their observations."\(^\text{74}\) The authors identified five subgroups from their sample of fifty respondents with sufficiently distinct points of view to preclude generalized results based on averaging procedures.

A further application of Tucker-Messick analysis was reported by Walters and Jackson. They found two distinct points of view among a group of respondents (one of a higher dimensionality than the other) in the way in which limited information is used to form an impression about another person. The authors report considerable surprise in finding only two distinct points of view in an exercise of this complexity.\(^\text{75}\)

In a different approach to individual difference analysis, Berlyne, Ogilvie, and Parham measured perceptual consistency by performing a two-way analysis of variance on similarity rankings gathered from two groups


of twenty subjects each. The authors reported finding high degrees of consistency among respondent groups.  

Few, if any, significant individual difference articles have appeared in psychological literature in recent years using either the Tucker-Messick points of view approach or the newer Carroll-Chang "shared-space" model.

The articles cited in this section have illustrated the use of MDS techniques in several areas of psychological research. The MDS algorithms have been used to gain a better understanding, not only of the way in which subjects perceive physical stimuli, but also of the factors which underlie or influence individuals' judgments of such abstract constructs as personality, social attitudes, and friendship. Furthermore, the application of various individual difference models in psychological research has been discussed.

The ability of the MDS technique to provide a coherent framework for the structuring of the individual perceptual process has led to the adoption of MDS and related methodologies within some business literature, especially in the science of market research. The following section will, therefore, detail empirical applications of multidimensional scaling in market research and related business areas.

B. Applications in Business Research

MDS techniques and applications began appearing in journal articles dealing with business research in the late 1960's. By far the majority of MDS applications in the business field have been reported by Paul Green

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76 Berlyne, Ogilvie, and Parham, op. cit.
and his associates at The University of Pennsylvania. They studied not only a variety of potential uses of MDS to help solve business-related problems, but also a number of methodological issues relating to the proper and efficient use of the MDS tool itself. Their results have been reported in a series of working papers, monographs, and journal articles. More recently, additional researchers have applied MDS to a wide range of business topics, although most applications still fall under the heading of "market research." The purpose of this section is to survey first the considerable contributions to the use and understanding of MDS techniques by Green and associates, and second a number of additional applications of MDS to business-oriented problems reported by more recent researchers in this area.

1. Contributions of Green and Associates

The initial application of multidimensional scaling to a business-related problem was a study of test market characteristics and selection techniques by Green, Frank, and Robinson. They utilized a variety of statistical data relating to a number of test market cities in order to derive indirect similarity measures which were then used to obtain homogeneous clusters of markets with similar properties. The authors argued that such a procedure allows the selection of test markets which contain desired characteristics or specific qualities required by the researcher, while at the same time increasing efficiency (and lowering costs) through the reduction of "redundant" or "overlapping" test situations.77

Two subsequent articles by Green, Carmone, and Robinson, and Frank and Green were primarily methodological in nature and served to introduce,  

classify, and describe various MDS techniques which were available at that time. The first article offers a brief discussion of both the historical development of MDS and its potential applications in marketing research, as well as demonstrations of the spatial configurations of stimuli which can be generated from both similarities and preference data.\(^7^8\) The second paper reviews various clustering algorithms, methodologies, and programs, as well as their usefulness in business research.\(^7^9\) In a subsequent paper, Green, Carmone, and Fox combined clustering procedures with MDS techniques to study individuals' perceptions of television programs. They derived the similarity rankings used as input to the scaling program from the frequency with which respondents "clustered" one program with another. Although the authors report reservations about this approach to gathering similarities estimates, it may be quite useful for research designs in which the number of stimuli to be scaled is quite large (i.e., \(n > 20\)).\(^8^0\)

Although a variety of substantive results have emerged from the articles produced by Green and his associates, contributions to the understanding and solution of a variety of methodological issues and problems in the application of MDS have continued to be the major results of their efforts. A primary concern has centered on the question of whether


stimulus configurations would be invariant across various data types or collection techniques. Green, Carmone, and Robinson collected both direct similarity judgments and indirect "confusions" data measuring individuals' perceptions of a set of eight national magazines. After comparing the stimulus configurations resulting from each data set, they reported that "the map derived from the confusions data generally agreed in dimensionality and configuration with that obtained from direct subjective measures of similarity."81 In another example, Green and Rao studied the stability of scaling solutions over differences in data collection methods and differences in the stimulus set. They concluded that a significant degree of similarity was exhibited between scaling solutions obtained from all types of data collection techniques and stimulus sets used in their experiment.82 Along similar lines, Green and Maheshwari observed the ability of widely used scaling programs to reproduce a known stimulus configuration using different data collection techniques or data which had been reduced in quality through the systematic introduction of ties or errors. The authors concluded that the use of conditional proximity data in well-known scaling programs provided a satisfactory replication of known stimulus configurations even with a large proportion of tied responses.


When random noise was introduced concurrently, however, the quality of the configuration replication declined rapidly.  

Several articles were concerned with additional methodological issues. Green and Carmone describe an experiment to compare the stimulus configurations of a set of graduate schools which resulted from the application of MDS to similarities judgments with configurations resulting from the "unfolding" of the same individuals' preference rankings. The authors reported substantial differences in the stimulus configurations resulting from the two scaling techniques, and attribute this to "the influence of differential weighting of 'perceptual' dimensions in the context of preference." A study by Green and Morris compares two well-known "individual difference" models, the Tucker and Messick "points of view" model and the Carroll and Chang "shared space" model. Generally similar results are obtained from each technique when applied to perceptual data concerning various musical artists gathered from a sample of undergraduate music majors and nonmusic majors. Nevertheless, Green argues that the Carroll model is more efficient and better suited "for the examination of the data's fine structure." In a related methodological article, Green and Rao discuss various proximity measures for use in clustering techniques and programs.

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Several articles have combined methodological surveys with initial attempts to generate substantive results. An early paper by Green and Carmone use factor analysis, cluster analysis, and MDS with the objective of both comparing techniques and providing information on the variables used by subjects to perceive and differentiate between various brands and models of computers. A subsequent Green and Carmone article examined differences in advertising perceptions between advertising "experts" and supposedly nonexpert students. Although perceptual differences between the two groups were discovered, attempts to "label" the perceptual axes or dimensions of either group were generally unsuccessful. A study by Green, Maheshwari, and Rao attempted to use MDS to determine the impact of self-concept on car brand perception and preference. Results in this study were generally inconclusive, which tended to refute several earlier (non-MDS) articles which used statistical tests to relate preferred brand characteristics to the individual's self-concept.

An important article, especially in relation to the techniques and objectives of the research reported in this dissertation, is an article by Green and Maheshwari describing stimulus configurations and joint spaces constructed from common stock stimuli. Their central objective was the determination of whether differing amounts and types of information available to an individual would change his perceptual configuration of a given

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stimulus set in a predetermined way. Although a wide variety of specialized techniques were used and results reported in an effort to show the versatility of MDS procedures, the following are the substantive results of this research into perceptions of common stocks:

(a) Both a return axis and a risk axis were identified in subjects' stimulus configurations. Although Green confined his analysis to two dimensions, it appeared that three dimensions were required to fully represent the respondents' perceptual patterns.

(b) Differences in "point of view" were identified for the two subject groups which received varying amounts of information relating to the stimulus set. Nevertheless, the manner in which perceptions differed between the two groups was not easily interpretable or directly related to the differences in information they received.

(c) Attempts to relate stimulus-ideal point distances to observable investment behavior (the selection of stocks for inclusion in hypothetical portfolios of varying size) were generally unsuccessful.  

Although certain of the questions studied by Green and Maheshwari are closely related to hypotheses of this research, important differences (and, of course, extensions) are present in this dissertation which could substantially modify Green's conclusions. Briefly, a few of the major differences in areas related to Green's work include (a) a respondent sample which consists of security analysts and portfolio managers rather than business students, (b) the use of risk and return definitions and measures which are considerably closer to those used by the financial community, and (c) considerable reliance on "aggregate" similarity or preference judgments in the testing of hypotheses. In addition to these basic modifications of experimental design, this research will study

Paul Green and Arun Maheshwari, "Common Stock Perception and Preference."
several hypotheses and potential uses of MDS in the context of portfolio selection models which were not considered by Green and Maheshwari.

Turning once again to methodological rather than substantive research, two recent articles by Green and his associates have examined both data collection techniques and the effects of individual differences on aggregate scaling configurations. In the first article, Green and Rao studied the interacting effects of a varying number of rating scales and a varying number of possible discriminations (intervals) along each scale in the recovery of a known stimulus configuration. Such results have considerable significance for the experimenter who wished to construct "indirect" measures of perceived inter-stimulus similarity. The authors report that rapidly diminishing returns in the quality of configuration replication set in with more than eight independent rating scales or more than six intervals per scale. It is possible, however, to offset, at least to some degree, a deficiency in the number of scales by increasing the number of possible intervals, and vice versa.  

In a second methodological article, Green and Rao studied the degree to which a known configuration could be recovered from the aggregated data of individuals who differ in their perceptions of the "target" configuration and that "recovery was nearly perfect for all methods."  

In summary, the works of Green and his associates have primarily consisted of tests of the MDS methodology itself, whether in relation to different methods of data collection, different programs for performing

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multidimensional scaling, or different approaches to axis interpretation and defining of individual points of view. As a final step in the development and understanding of MDS methodology, Green has combined his knowledge of the MDS technique as well as virtually all his previous empirical results into a monograph designed to explain the development of scaling algorithms and the versatility of this experimental tool. Included are simulation tests of the most recently developed and widely used MDS programs, discussions of individual difference and clustering models, and a complete listing of computer programs available for a variety of MDS techniques and applications.  

Although Green and associates have been by far the most prolific users of MDS in a business context, within the past few years other writers have contributed methodological and substantive MDS results within the context of business research. Once again, virtually all applications of MDS are found in literature relating to market research. The following section will discuss several of these articles.

2. Other Business Applications of MDS

An early application of MDS to a business-related problem was reported by Doehlert in a study of automobile colors. He attempted to determine which colors prove most attractive to prospective car buyers by placing both color and individual "ideal points" in the same perceptual space, then drawing conclusions about which colors are "best" for autos from the distribution of points. He also discusses the usefulness of

93 Paul E. Green and Frank J. Carmone, Multidimensional Scaling and Related Techniques in Marketing Analysis (Boston, Massachusetts: Allyn and Bacon, Inc., 1970.)
the MDS approach in isolating market segments and aiding new product development.  

Two articles by Taylor classify scaling models and appropriate data collection techniques. The first is largely a replication of Coombs' approach which is based on the nature of the proximity judgments obtained from respondents. In addition he presents an interesting but brief discussion of the uses of the MDS configuration in drawing conclusions about human behavior.  

A second paper discusses a variety of methods for obtaining similarities data for input into MDS models on the basis of the numbers of judgments a respondent must make under each technique.  

Cook and Hernifer present a simulation model for the prediction of demand for a new product based on an individual's purchase history and his current preferences. The core of their model is the use of MDS to test hypothesized relationships between "expressed and revealed individual preference" within a perceived attribute space. In their model, the authors assume a correspondence between the rank order of expressed preference for a product and actual purchase behavior.  

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Steffire explicitly details the concept of market segmentation by perceived similarities of products rather than by physical attributes of the product or demographic attributes of the customer. While not concerned specifically with MDS techniques, his discussion includes such familiar MDS concepts as individual differences in perceptions, relating preference data to similarities judgments, obtaining the "dimensions" of similarity, and discovering efficient methods of gathering similarities and preference data. 98 Barnett integrated Steffire's proposals for a strategy of market segmentation with a discussion of several multivariate techniques, including MDS. 99

Two applications of MDS to market research problems were discussed first by Neidell, then by Neidell and Teach. In the first article, Neidell provides an interesting illustration of the MDS technique in which several cities are properly located on a map of the United States by an MDS program which knows only the inter-city distances. He also discusses axis labeling, cluster analysis, and market segmentation in the context of a stimulus sample of ethical drugs. 100 Neidell and Teach attempt to develop a predictive model for the purchase of a convenience good (toothpaste). Using entirely indirect data collection techniques, they were


able to closely predict the market shares of given toothpaste brands from the scaling of respondent similarity and preference judgments.\textsuperscript{101}

Finally, two recent marketing applications of MDS are worthy of mention. Turner discussed various ways of obtaining similarity judgments from salesmen to allow the construction of a customer configuration. His ultimate objective was to combine this result with preference data to predict the "calling effort" made by salesmen to various customers. His results were, at best, inconclusive.\textsuperscript{102} Klahr reported a largely methodological exposition of the usefulness of MDS in structuring individuals' perceptions of cigarette brands. Although substantive results were highly tentative (i.e., only ten subjects were used) he provides a succinct description of several elementary forms of analysis of MDS results which can highlight important aspects of both individual and group perceptual structures.\textsuperscript{103}


and application of multidimensional scaling techniques. The classification scheme used in this summary of relevant MDS literature has been as follows:

1. An examination of the development of MDS theory and algorithms over time.

2. A review of significant empirical work in the behavioral science areas, especially psychology.

3. A review of recent developmental and empirical results from the application of MDS techniques to business-oriented research problems.
CHAPTER III

METHODOLOGY

The purpose of this chapter is to present the experimental design and evaluative techniques used to confirm or deny the hypotheses presented in Chapter I. As described previously, the basic data utilized in MDS-based research are individual judgments of "similarity" or "dissimilarity" between pairs of objects or "stimuli." Thus, Chapter III will discuss the selection of the two lists of well-known common stocks used as stimuli, the design of the two basic questionnaires used to gather data for this research, and the selection of the four respondent groups to whom questionnaires were sent. In addition, a description of the specific MDS models, computer algorithms, and related techniques to be used in the evaluation of the hypotheses of this study will also be presented.

I: DATA COLLECTION

A. Stimuli Selection

Two lists of eleven well-known common stocks were selected as the basic stimuli in this research (i.e., objects which could be compared to one another in terms of "similarity"). One list was designated the "chemicals" list since it consisted of eleven companies commonly considered as belonging to the chemical industry. The second list of stocks was designated the "diversified" list, since the names on it belonged to a variety of industry groups. Table 1 lists the companies belonging to each group.
| TABLE 1 |
| COMMON STOCK STIMULI |

A: "CHEMICAL" LIST

1. Pittsburgh Plate Glass
2. Allied Chemical
3. Diamond Shamrock
4. DuPont
5. Minnesota Mining & Manufacturing
6. Monsanto
7. Dow Chemical
8. Celanese
9. Union Carbide
10. Commercial Solvents
11. Koppers

B: "DIVERSE" LIST

1. International Business Machines
2. Standard Oil of New Jersey
3. American Telephone & Telegraph
4. Polaroid
5. Avon Products
6. Burroughs
7. Minnesota Mining & Manufacturing
8. Insurance Company of North America
9. Warner-Lambert Pharmaceuticals
10. American Airlines
11. Sears-Roebuck
Selection of companies for the chemical and diversified lists was made with two considerations in mind. First, it was desirable to select companies whose nature and investment characteristics would be as familiar as possible to respondents. This increases the meaningfulness of the judgments of similarity and dissimilarity obtained from individuals regarding the investment nature of these firms and their securities. Second, it was desirable to choose a group of securities with as broad and diverse a background of investment characteristics as possible in order to insure that respondents might have the opportunity to differentiate between pairs of securities on the basis of all possible salient investment dimensions.

The eleven common stock names comprising the diversified list were randomly selected from "Vickers Favorite Fifty" as of December, 1971. Respondent familiarity was immediately assured, and the selected list contained sufficient diversity in terms of industry category and recent investment experience to allow for meaningful dissimilarity judgments.

Providing a broad range of investment characteristics or recent investment experience among the stocks included in the chemicals list posed a slightly greater problem, since all the candidates were drawn from a single industry category. To help provide diversity among the chemical stocks, the results of a recent paper by Elton and Gruber were utilized. The authors utilized principal components techniques and cluster analysis to group a variety of companies on the basis of financial and investment

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1 Barton M. Biggs, "Vickers Favorite Fifty," Barrons, January 20, 1972, p. 3.

similarity rather than by standard industry labels. Their reported results showed that twenty-three companies commonly assigned to the "chemical" industry were not at all homogeneous in terms of their financial or investment nature, but were, in fact, distributed through eight different "pseudo-industries" defined by clustering techniques. Thus, to provide maximum diversity within the chemical list of stocks used as stimuli in this research, companies were chosen so that all possible pseudo-industries defined by Elton and Gruber were represented in the final list of eleven "chemical" companies. 3

B. Questionnaire Design

Each list of eleven common stocks formed the basis for the design of both an initial questionnaire and a follow-up questionnaire which was sent to respondents after the first had been completed and returned.

The initial questionnaire was the instrument by which basic similarity-dissimilarity judgments between all possible pairs of common stocks on one of the two lists were obtained. Although a variety of data collection techniques and approaches to questionnaire construction have been developed and used in multidimensional scaling studies, "direct" similarity-dissimilarity judgments comprised the primary data in this research. Specifically, each respondent received an initial questionnaire in which he was asked to do the following:

1. For each of the fifty-five possible pairs of common stocks on a given list ("chemical" or "diverse") assign an integer rating on a nine-point scale ranging from "very similar" (=1) to "very dissimilar" (=9) depending on the perceived similarity between the investment characteristics of the two securities. Respondents were informed that criteria for judging similarity were entirely up to the individuals, but that an attempt should be made to be consistent over all paired comparisons.

3 The list of eleven chemical stocks is spread over eight of Elton and Gruber's pseudo-industries, with three represented twice.
2. After making the judgments described above, provide a list of the criteria utilized in judging relative similarity.

3. Rank the list of eleven common stocks used as stimuli in terms of preference (current investment merit) from 1 (= most desirable under today's market conditions) to 11 (= least desirable).

4. Indicate the relative importance in the respondent's investment decisions of several security attributes or characteristics by which the merit of an investment alternative might be judged.

5. Select an optimum portfolio totaling $10 million from the list of common stocks used as stimuli in the questionnaire. Respondents were instructed to select as many or as few of the questionnaire (chemical or diverse list) stocks as they desired.

6. Provide minor demographic data about themselves and their jobs and indicate estimated market levels during the subsequent twelve months to the completion of the questionnaire.

Each of the two forms of the initial questionnaire is shown as Appendix A and B. Appendix A contains the "chemical" questionnaire; the design which obtains similarity judgments on all possible pairs of stocks from the chemical list. Appendix B shows the "diverse" questionnaire which is identical to the "chemical" except that pairs of securities are drawn solely from the diverse list of stocks discussed earlier.

Each respondent completed a single initial questionnaire, either of the chemical or diverse format. After returning his completed initial questionnaire, each respondent was sent a "follow-up" questionnaire. Once again, two distinct forms of follow-up questionnaires were needed to conform to the two lists of common stocks on which the initial forms were based. Appendix C shows the follow-up questionnaire based on the chemical list, while Appendix D shows the format of the "diverse" follow-up instrument. The format of the follow-up questionnaire a respondent received
(i.e., "chemical" or "diverse") corresponded to the type of initial questionnaire he completed.

The purpose of the follow-up questionnaire was to obtain respondents' rankings of the common stocks used as stimuli from highest (= 1) to lowest (≈ 11) in terms of ten attributes commonly considered important in investment decisions. The ten dimensions along which the stock lists were ranked corresponded to the attributes ranked by importance to the individual in Part 4 of the initial questionnaire. This data is the "subjective" perceptual information to be used in the attempt to label the axes of the configuration spaces generated from the similarity judgments obtained earlier. More will be said concerning the use of this data in the discussion of H₄ later in this chapter.

The primary purpose in using both an initial and a follow-up questionnaire was twofold:

1. It was expected that the sheer size and bulk of a single questionnaire would have a negative impact on the response rate, even though respondents were contacted before questionnaires were mailed.

2. It was felt that the number of responses required from each subject might lead to fatigue and loss of accuracy if all necessary information were to be gathered at one time in a single questionnaire. For these reasons, the "initial" and "follow-up" format was chosen for the gathering of questionnaire data.

C. Statistical Data

In addition to the perceptual or judgmental data gathered directly from respondents via the questionnaires, additional statistical data concerning each of the twenty-two common stocks used as stimuli was also obtained. This data was used primarily in the attempt to "label" the
axes of the various individual and group configuration spaces which were generated.

Two sources of statistical data for the common stocks were utilized. Forbes magazine, in its Annual Report on American Industry 4 provided the following information for each stock:

(a) Five-year average return on equity
(b) Five-year average return on total capital
(c) Five-year average annual sales growth
(d) Five-year average annual earnings per share growth
(e) Total five-year stock price growth

In addition to the variables listed above which could influence an individual's investment decision, a variety of statistical measures of return and risk have been used or proposed for use in normative security selection models. These measures were calculated for each of the twenty-two common stock stimuli. Five years of monthly stock price data was gathered for each company and used as input to the RISK computer program developed by Dr. Roger Harvey of The Ohio State University. This program calculated the following statistics for each stock: 5

Measures of Return

(a) One-year arithmetic average monthly return
(b) One-year geometric mean monthly return
(c) Five-year arithmetic average monthly return
(d) Five-year geometric mean monthly return

Risk Measures

(a) One-year standard deviation of monthly returns
(b) One-year coefficient of variation of monthly returns
(c) One-year semi-standard deviation of monthly returns
(d) One-year modified quadratic mean monthly returns
(e) One-year log deviation of monthly returns
(f) One-year mean absolute deviation of monthly returns


5 Formulas for the calculation of these measures are shown in Appendix E.
(g) Five-year standard deviation of monthly returns
(h) Five-year coefficient of variation of monthly returns
(i) Five-year semi-standard deviation of monthly returns
(j) Five-year modified quadratic mean monthly returns
(k) Five-year log deviation of monthly returns
(l) Five-year mean absolute deviation of returns

The financial variables gathered from Forbes, the statistical risk and return measures described above, and the subjective rankings of the common stock stimuli on the basis of the attributes listed in the follow-up questionnaire form the "property vectors" to be used in the labeling of the axes of the configuration spaces generated from similarities judgments.

D. Selection of Respondents

As discussed earlier in Chapter I, four distinct groups of respondents were selected to complete either a "chemical" set or a "diverse" set of initial and follow-up questionnaires. The four subject groups were comprised of (a) one group of security analysts who specialized in the chemical industry, (b) one group of security analysts whose specialities or areas of concentration lay in some areas other than chemicals, and (c) a single group of portfolio managers divided by random selection into two equal subgroups. All respondents were initially identified through the assistance of Mr. Herschel Pittenger of the Ohio State Teacher's Retirement System. All respondents are employed as analysts or portfolio managers by major brokerage firms or investment houses. All were contacted before initial questionnaires were sent to confirm the willingness of the individuals and their employers to participate in this research. This pre-contact effort also helped insure a high response rate to the mailed questionnaires.

Three of the groups described above received initial and follow-up questionnaires based on the chemical list of common stocks. These
included both security analyst groups ("chemical analysts" and "non-chemical analysts") as well as one of the two groups of portfolio managers ("portfolio manager-chem"). The second group of portfolio managers ("portfolio managers-diverse") received questionnaires built around the diversified list of stocks.

While it was not considered essential that all groups contain an equal number of respondents, a sample size of from fifteen to twenty in each group was considered desirable and sufficient to judge basic differences and similarities within as well as between broad groups of market participants. The original identification of potential respondents resulted in initial questionnaires being mailed to sample groups of the following sizes:

Chemical Analysts (16)  
Non-Chemical Analysts (20)  
Portfolio Manager-Chemical (17)  
Portfolio Manager-Diverse (17)

As shown above, a total of seventy initial questionnaires were mailed. Ultimately sixty-six were returned. Of these, four were judged unacceptable for inclusion, either because of serious omissions or because of obvious lack of concern for accuracy (i.e., all pairs of stocks ranked identically in terms of similarity). Thus, the final, usable sample of initial questionnaires which formed the basis for the results of this study totals sixty-two, distributed over the four respondent groups as follows:

Chemical Analysts (13)  
Non-Chemical Analysts (19)  
Portfolio Manager-Chemical (15)  
Portfolio Manager-Diverse (15)

Follow-up questionnaires were mailed to all subjects whose initial completed questionnaires were judged acceptable. From the sixty-two
follow-up probes which were mailed, fifty-six were returned, of which three were judged unacceptable. The final total of fifty-three follow-up questionnaires was distributed over the four respondent groups as follows:

- Chemical Analysts (12)
- Non-Chemical Analysts (16)
- Portfolio Manager-Chemical (13)
- Portfolio Manager-Diverse (12)

Figure 5 summarizes the basic experimental design used in this research. As is shown, three groups responded to questionnaire sets (initial and follow-up) based on the chemical list, and one to questionnaires using the diverse list of stocks. The numbers under the group headings show the total initial and follow-up questionnaires which were ultimately used in the evaluation of the hypotheses of this research.

II: HYPOTHESIS TESTING

The following discussion will outline the methodology by which the basic data gathered as discussed above will be utilized to confirm or deny the hypotheses postulated in Chapter I. Included in this section will be brief discussions of the multidimensional scaling (MDS) and related programs which were used in this research.

Hypothesis 1 examines multidimensional scaling solutions and configuration spaces on an individual basis. Hypothesis 2 is concerned with determining the nature and degree of perceptual differences which exist between important groups of market participants from whom responses were gathered. Hypothesis 3 examines the consistency of judgments and perceptual patterns within the groups themselves. Hypothesis 4 attempts to apply specific labels to the dimensions or axes of aggregate configuration spaces defined for respondent groups. Finally, Hypothesis 5 combines the descriptive models of investor perception defined in the
FIGURE 5

EXPERIMENTAL DESIGN SHOWING INVESTOR GROUP
VS. QUESTIONNAIRE COMBINATIONS

All Respondents
(62)

Security Analysts
(32)

Chemical Analysts
13:12

Non-Chemical Analysts
19:16

Portfolio Managers
(30)

Port. Man.- Chemical
15:13

Chemical Questionnaire

Port. Man.- Diverse
15:12

Diverse Quest.
evaluation of earlier hypotheses with preference data gathered from respondents to create and evaluate both individual and group predictive investment selection models.

H: The configuration of the stimulus set will be represented by a space of low dimensionality (i.e., at most, three dimensions).

The initial step in the evaluation of this hypothesis will be the submission of the basic similarities judgment data from each individual initial questionnaire to Version 8-MP of Kruskal's M-D-SCAL multidimensional scaling program, developed by D.D.S. Poor of The Ohio State University. This program uses the \( n(n - 1)/2 \) similarity judgments available from all possible pairs of \( n \) stimuli to find a set of coordinates \( X_{ia} (i = 1, 2, \ldots n; a = 1, 2, \ldots m) \) in \( m \)-dimensional space which minimizes a "stress" measure defined by Kruskal as

\[
\text{Stress} = S = \sqrt{\frac{\sum_{i,j} (d_{ij} - \overline{d}_{ij})^2}{\sum_{i,j} (d_{ij} - \overline{d}_{ij})^2}}
\]

In the Kruskal "stress" measure \( d_{ij} \) denotes the distance from \( X_i \) to \( X_j \) in Euclidean space, \( \overline{d}_{ij} \) is the arithmetic average \( d_{ij} \), and the \( \overline{d}_{ij} \) are the predicted values of \( d_{ij} \) resulting from a regression of interpoint distances on the initial similarities data.

Kruskal's stress measure is an indicator of the "badness of fit" of a given scaling configuration in a space of given dimensionality. The M-D-SCAL program initially identifies the stimulus configuration which

\[\text{footnotes 18 and 31 of Chapter II.}\]

\[\text{In this study } n(\# \text{ of stimuli}) = 11; \text{ thus } n(n - 1)/2 = 55.\]
minimizes stress in the space of the lowest dimensionality (usually 1) desired by the researcher. The program then repeats this process in as many additional dimensions as are desired or as are required to reduce stress (i.e., increase the fit between the data and the configuration space) to acceptable levels. Kruskal has provided the following guidelines for evaluating the goodness of fit of a given stimulus configuration:²

<table>
<thead>
<tr>
<th>Stress</th>
<th>Goodness of Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>40% and up</td>
<td>Poor</td>
</tr>
<tr>
<td>20% to 40%</td>
<td>Fair</td>
</tr>
<tr>
<td>10% to 20%</td>
<td>Good</td>
</tr>
<tr>
<td>5% to 10%</td>
<td>Excellent</td>
</tr>
<tr>
<td>0% to 5%</td>
<td>&quot;Perfect&quot;</td>
</tr>
</tbody>
</table>

Additional information concerning the degree of diversity between the points of view of respondent groups will be obtained through the application of the Tucker-Messick "VIEWS" individual differences computer program.³ The VIEWS procedure begins with the determination of a row vector for each individual which consists of similarity judgments on each of the n(n - 1)/2 possible pairs of n stimuli. After identical data is obtained for each of N individuals, an N x N symmetric correlation matrix of individual judgments is then calculated. This matrix is then factor analyzed by principal components. The component "scores" of each subject can be considered to represent individual "person points" in the component "space." At this point, two approaches may be used to observe

differences in "points of view." The first is to observe the relative proportions of the total data variation "accounted for" by the first few principal components. The number of principal components required to account for a substantial portion of the total variation in the data is an indicator of the diversity of "points of view" represented by the basic data and, thus, of the homogeneity of perceptual patterns.

The second approach is to attempt to "cluster" individuals on the basis of the component "scores" discussed above. This can be attempted visually or with the use of one of a variety of numerical clustering routines available as computer programs.

In this research, both VIEWS-related approaches to the identification of perceptual differences between groups will be employed. First, the 1 x 55 vector of similarities judgments for each possible pair of stimuli will be obtained from each individual. Individual vectors will then be aggregated to form matrices corresponding to the initial respondent groups (i.e., the chemical analyst matrix will be dimensioned 12 x 55, the non-chem matrix 19 x 55, etc.). Each possible pair of respondent-group matrices will then be submitted to the Tucker-Messick VIEWS program in order to determine the number of principal components required to represent the variation in the data (i.e., the number of different "points of view" which are present). A visual analysis of the resulting plot of component "scores" for each individual will indicate the degree to which different "points of view" are associated with different respondent groups or cut across the boundary lines between groups.

As an additional analytical approach toward measuring the significance of perceptual differences between respondent groups, individuals will be "clustered" on the basis of their similarities judgments through
the use of the Ward Hierarchical Clustering Routine, as modified by
Dr. Youngman of the Department of Geography, The Ohio State University.
The clustering algorithm used in this case is described by Ward as
follows:

The grouping procedure reported here is based on the
premise that the greatest amount of information, as
indicated by an objective function, is available when
a set of \( n \) members is ungrouped. Hence the grouping
process starts with these \( n \) members, which are termed
groups, or subsets, although they contain only one
member. The first step in grouping is to select two
of these \( n \) subsets which, when united, will reduce by
one the number of subsets while producing the least
impairment of the optimal value of the objective
function. The \( n - 1 \) resulting subsets are then ex-
amined to determine if a third member should be united
with the first pair or another pairing made in order
to secure the optimal value of the objective function
for \( n - 2 \) groups. This procedure can be continued,
if desired, until all \( n \) members of the original array
are in one group. Since the number of subsets is
systematically reduced (\( n, n -1, \ldots, 1 \)), the process
is termed "hierarchical grouping" and the resulting
mutually exclusive groups "hierarchical groups."\(^{10}\)

Individual multidimensional scaling configurations of from one to
five dimensions will be calculated for each respondent from the judgments
of "similarity" he provides between the fifty-five pairs of stocks listed
on the initial questionnaire. It is anticipated that no more than five
dimensions will be required to produce essentially "perfect" fits between
subjective similarities judgments and the resulting multidimensional
scaling configurations. Furthermore, even fewer dimensions should be re-
quired to obtain "excellent" fits (i.e., stress below 10%). The exami-
nation of this interaction between stress levels and configuration
dimensionality for each respondent will allow initial judgments to be

\(^{10}\) Joe H. Ward, Jr., "Hierarchical Grouping to Optimize an Object-
ive Function," *Journal of the American Statistical Association*, LVIII
(March, 1963), 236-244.
made concerning individual perceptual dimensionality and the consistency of perceptual dimensionality within the various respondent groups.

H₂: Significant differences exist between the perceptual patterns of various groups of market participants.

The primary objective of the research methodology discussed in this section is to systematically identify differences in perceptual pattern or "point of view" between the important market groups from which subjects were drawn. The observation of the consistency of perceptual configurations among the members of the respondent groups surveyed is the subject of Hypothesis III.

Of initial concern will be differences in the dimensionality of common stock perceptions demonstrated by the various groups of respondents. In order to examine this question Kruskal stress values for configurations of from one to five dimensions will be averaged over the individuals in each group of respondents. Observations of the patterns of descending average stress values as dimensions increase as well as the number of dimensions required to pull average stress values into the range considered to show "excellent" fits (i.e., stress less than 10%) will indicate any significant differences in perceptual dimensionality between subject groups.

For the purposes of this research, individual similarities judgments will be submitted initially to a normalization program to standardize the data. The resulting standard variates will then be used as the basic input data to the Ward Clustering Program. The objective function which is calculated and optimized at each stage of the hierarchical clustering will be the error sum of squares (ESS) measure given by

$$ESS = \sum_{i=1}^{n} x_i^2 - \frac{1}{n} \left( \sum_{i=1}^{n} x_i \right)^2$$

where $x_i$ is the "score" of the $i$th individual. Since the clustering
will be done on the basis of 55 "variables" (i.e., the similarity judgments on each of fifty-five pairs of stocks), \( X_i \) is, technically, the \( 1 \times 55 \) vector of similarity judgments for subject \( i \).

The first stage of the clustering analysis will utilize all sixty-two respondents from whom satisfactory initial questionnaires were obtained. Standardized variates obtained from all subjects through the normalization of individual similarity judgmental data will be submitted to the Ward Clustering Program and related interpretive programs. The result will be a hierarchy of clusters, containing from one to sixty-two subjects, along with associated values of the objective function defined above for each level of clustering. The purpose of this analysis is not to define specific clusters of individuals for further study; rather it is to determine the extent to which groups of individuals defined on the basis of similarity of perceptual patterns match the four respondent groups defined earlier by occupation or stimulus set. The degree to which individual memberships in the four best "clusters" defined by the Ward algorithm are consistent with those in the respondent groups will indicate the significance of perceptual differences among these important groups of market participants. In addition, the Ward Clustering Routine will be applied to the similarity judgments gathered from the members of various pairs of respondent groups. Such clustering calculations can identify significant differences in the perceptual patterns of the four investor groups.

The preceding approaches to the identification of differences in respondent group common stock perceptual patterns have generally emphasized the magnitude of differences or similarities rather than their nature. It should be noted that the evaluation of \( H_4 \) will include a
comparison of the variables (dimensions) used by different groups to evaluate common stock investments, and that the discussion of H3 will include an examination of systematic differences in preference for common stock investment alternatives between the various respondent groups.

H3: Significant "clusters" of individuals within the larger sample groups can be identified as having similar perceptual judgments or patterns in relation to the stimuli set.

The procedures discussed earlier in the evaluation of H1 and H2 were aimed at the identification of the nature of individual perceptual patterns (H1) and with systematically discerning the degree to which major market groups differ in the ways they view and evaluate common stocks. H3 is concerned with the degree to which the different respondent groups sampled in this research can be considered "homogeneous" in terms of the manner in which they perceive investment alternatives.

The Tucker-Messick VIEWS program will be used initially in the attempt to judge the homogeneity of similarity judgments among all members of individual respondent groups. This procedure used the N x 55 matrices of similarity judgments constructed in the evaluation of H2 (where N is the number of subjects in a given respondent group) to arrive at an N x N symmetric matrix of intersubject rank order correlation coefficients for all members of a given group. The Tucker-Messick algorithm then performs a principal components analysis of this matrix.

As discussed above under H2, the presence or lack of homogeneity among subjects is then indicated by the percentage of total variation in the data "explained" by the first or the first few principal components. If more than one "point of view" is indicated by the principal components result, then the plotting of component "scores" should provide indications of both the membership in and of the "tightness" of the subgroups to be found within the larger respondent group.
A second approach to the identification of subgroups with distinct points of view will be to utilize Ward's Hierarchical Clustering Routine on the basic similarities judgments of all members of a single respondent group. Of interest in this analysis is not only the membership of subgroups identified, but also the value of the optimal objective function at each level of clustering. The error sum of squares calculation performed at each level of grouping can be considered as the "loss of information" which occurs as individuals are aggregated into groups. The minimum value of this function, 0.0, occurs when each individual is treated as a separate cluster; the maximum when all individuals are included in one single cluster. The "significance" of intermediate levels of clustering between these two extremes can be determined by observing the change in the "information" function as the number of clusters increases. This research will determine whether any of the respondent groups surveyed can be better understood or described in terms of one or more subgroups containing individuals with homogeneous "points of view." If clusters of individuals such as these are discovered within any or all respondent groups, further comparisons and analyses will be made on an inter-cluster basis. If none are found, the original respondent groups will be considered sufficiently homogeneous to permit the aggregation of individual judgmental data into single configuration spaces which adequately represent the points of view of all individual group members. Either approach permits further comparisons and analyses to be made on an inter-group basis rather than on an inefficient and laborious inter-individual basis. The specific methodology by which a number of individual similarity judgments are combined to form a "group" configuration space will be discussed below along with the methodology to be used in the evaluation of H4.
H₄: Assuming stimulus configurations are generated containing a minimum of two dimensions, both a "return" and a "risk" axis will be identified.

In the discussions of the research methodology to be used beyond this point, it will generally be assumed that analyses will be performed on configuration spaces and judgmental data which represent the combined or summarized estimates of groups of individuals with similar perceptual patterns. The identification of these groups is the subject of the research discussed earlier under H₂ and H₃. Although working with a small number of relatively homogeneous groups of individuals is a far more convenient and efficient approach to modeling investor behavior, most of the basic methodologies and algorithms to be discussed below would be readily applicable to an individual-by-individual evaluation of the hypotheses of this research.

In the subsequent discussion, then, it will be assumed that "clusters" of individuals, defined either at the respondent group level (i.e., all chemical analysts, all non-chemical analysts, etc.) or at subgroup level will have been identified. Once this is done, a "group" configuration space for each cluster of individuals will be defined by submitting the basic similarity-dissimilarity judgments from all individuals in a given group to the Carroll-Chang INDSCAL computer program.¹¹

As noted earlier in Chapter II, the objective of the INDSCAL technique is to create a single "shared" perceptual space for a group of subjects and to allow individual differences in perception to be identified by the differing "weights" assigned by various subjects to the dimensions

of the group space. Although additional clustering or grouping of individuals is sometimes performed on the basis of these axis weightings, such analysis should not be necessary in this research because of the already assumed homogeneous nature of similarity perceptions within the groups of respondents submitted to the INDSCAL program. What will be achieved through this analysis is a single configuration, in as many dimensions as desired, which can be said to represent as accurately as possible the common shared perceptual space of a homogeneous group of respondents.

Of considerable importance as well is the fact that the INDSCAL program provides a group configuration space whose axes or dimensions are uniquely determined. As reported by Wish and Carroll:

In solving for the stimulus coordinates and dimension weights the program finds the particular orientation of axes that maximizes the goodness-of-fit measure; that is, INDSCAL uses information latent in the variation among matrices to orient the dimensions uniquely. These axes, or dimensions, have a special status in INDSCAL and might be assumed to correspond to fundamental psychological processes that have different saliences for different individuals. 12

Because of this important characteristic of INDSCAL group scaling solutions, further analyses of and comparisons between the various respondent group spaces constructed in this research can be carried out with a high degree of confidence without concern for additional rotation or location of configuration axes.

After a single stimulus configuration is defined for each respondent group, the process of "labeling" the perceptual dimensions will begin. As noted earlier in this chapter, potential axis labels will consist of:

(a) The list of ten potentially important investment attributes contained in the follow-up questionnaire by which each of the eleven common stock stimuli were ranked.

(b) The various statistical return, risk, and growth measures for each common stock described earlier in this chapter.

The respondents' subjective rankings of the common stocks in terms of each of the attributes included in the follow-up questionnaire will be averaged across all members of the homogeneous respondent groups identified earlier. Combining these results with the objectively measured statistical data for each stock will result in a series of "property" vectors, or unidimensional return, risk, growth, and other scales along which each common stock will be assigned a unique value. Some of the property variables will originate in subjective (questionnaire based) date, while others will be developed objectively from outside statistical data.

The most common technique for assigning "labels" to the axes of a stimulus configuration is called the "max r" procedure. This method involves finding, for each property vector, a direction (vector) in the stimulus space located such that stimulus point projections onto the vector are maximally correlated with the candidate property vector's scale values for those stimuli. Figure 6 illustrates the potential result of such a "fitting" procedure. In this case, property vector 5 should provide the label for the vertical axis, while property vector 1 seems most highly correlated with the horizontal axis. The several scales which are far from being collinear with any configuration axis are often interpreted as composites of the basic dimensions.

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Carroll and Chang's PROFIT computer program\textsuperscript{14} will be used in this research to locate or place the direction vectors in the configuration spaces defined for each of the homogeneous respondent groups by the INDSCAL procedures discussed earlier. The list of property vectors used in dimensional interpretation will be broken into two groups; those "subjective" estimates of security return and risk characteristics gathered from the follow-up questionnaire, and the "objective" measures of security attributes calculated from outside statistical data. Correspondingly, the fitting of the property vectors and the attempt to label configuration axes of the group spaces will be done in two steps. First, an attempt will be made to label the dimensions using only the "subjective" perceptual property vectors. This process will provide important information concerning the security attributes and characteristics used by various respondent groups to evaluate and differentiate between alternative common stock investments. Systematic differences in the importance of different perceptual attributes between respondent groups will also be observed. In essence, this process will provide explicit information on the specific variables which affect and, to a large degree, determine investment behavior.

The second stage in the dimensional interpretation process will be to judge the usefulness of the "objective" property vectors as potential axis labels. Two major questions may be answered in this context:

(a) Which "objective" measures are most highly correlated with the perceptual dimensions of the configuration spaces of the various subject groups? In a sense, this question is aimed at determining which statistical

\textsuperscript{14} Jih-Jie Chang and J. Douglas Carroll, "How to Use PROFIT, A Computer Program for Property Fitting by Optimizing NonLinear or Linear Correlation," Bell Telephone Laboratories, Murray Hill, New Jersey, March, 1969. (Mimeographed.).
measures of a security's characteristics most closely correspond to the "perceptual" variables used by individuals to differentiate between common stock alternatives.

(b) How much information (if any) concerning a group's configuration space is lost when "objective" axis labels are substituted for "subjective" labels? That is, can we understand or describe a group's common stock perceptual patterns just as well on the basis of statistical measures derived from historical data as we can with "perceptual" labels gathered from the respondents themselves?

The importance of obtaining satisfactory axis labels for each respondent group from the outside, objective data takes on special significance in light of the ultimate objective of this research; the development of predictive investment selection models for important groups of market participants. Successful labeling of the configuration space dimensions with objectively measurable variables will satisfy one objective of this research; the construction of accurate descriptive models of the manner in which various groups of market participants perceive and differentiate among common stock alternatives. The methodology by which the descriptive models built under $H_4$ can be extended into predictive models of investment behavior will be discussed below in the testing of $H_5$.

$H_5$: An inverse relationship exists between stimulus-ideal point distances in an individual or group "joint space" and the degree of preference for a given security exhibited by individuals or groups in the construction of hypothetical portfolios.

In addition to the direct similarity-dissimilarity judgments obtained from the initial questionnaire, respondents were also asked to provide preference rankings for each stock and, in a later section of the initial questionnaire, the name and amount of each common stock he would include in an investment portfolio of $10$ million dollars. This preference data (either from a single individual or aggregated over members of a respondent group) can be combined with a configuration
space (derived, once again, from either individual or group data) to construct a "joint space" of both stimulus and ideal points. (As described earlier, ideal points are interpreted as possessing that combination of attributes which would be considered "ideal," or most preferred, by an individual or respondent group).

The most versatile computer program for the construction of "joint" spaces of perceptual and preference data uses an "unfolding" model developed by Carroll and Chang.\(^{15}\) This program, named PREF-MAP, combines the coordinates of the scaling configuration of similarities data (as performed, in this research by either the MDSCAL or INDSCAL programs) with the preference data from either a single individual or a group of respondents. The PREF-MAP algorithm then finds the ideal point position (or, in one case, vector) of each subject on the basis of four different alternative utility models or "phases." The four phases differ in their assumptions concerning the homogeneity of perceptual patterns and in the allowance of differential "stretching" or rotation of the axes of the configuration. The appropriateness of each alternative model in describing the preference patterns and derived utility functions of each individual is measured by the calculation of "goodness of fit" statistics as well as F-ratios between the various "phases" of the PREF-MAP routine.

The PREF-MAP program will be used in this research in three different ways to construct joint stimulus-ideal point spaces and to use these results in developing and evaluating predictive models of investment behavior. First, individual joint spaces will be constructed for

each respondent. That is, each subject's preference ratings will be combined with the coordinates of his own individual configuration space from the earlier MDSCAL results to form a unique joint space for each respondent. A possible result of an analysis of this type is shown in Figure 7. The distance from an individual's ideal point to each stimulus point is assumed to be an inverse function of the degree of preference the subject feels and will exhibit in an investment situation. This assumption will be tested for each individual by comparing the mean stimulus-ideal point distances for those securities selected for inclusion in his hypothetical portfolio with the comparable distances for those stocks not chosen. If the individual joint space configuration for each subject is useful as a predictive model of investment behavior, the stocks chosen for the individual's portfolio should have mean stimulus-ideal point distances significantly less than those of securities not selected.

Once the predictive ability of the PREF-MAP results are evaluated in terms of individual investment behavior, the feasibility of aggregating perceptual and preference data in order to develop predictive models for the larger groups identified earlier will also be determined. Two different approaches to the construction of "group" joint spaces will be employed. Both methods will use the group configuration spaces developed earlier via the INDSCAL program.

First, individual preference data will be combined with the coordinates of the "group" configuration space from earlier INDSCAL results to formulate a single "joint space" in which a unique ideal point is located for each member of the given respondent group. By comparing each subject's actual investment "selections" with predicted behavior based on the calculated distances between his ideal point and the group
FIGURE 7
HYPOTHETICAL PREF-MAP RESULT RELATING INDIVIDUAL
IDEAL POINT "A" TO COORDINATES OF STIMULUS
SECURITIES (POINTS 1-6)
space stimulus coordinates, the degree to which predictive accuracy is lost when the single group space is substituted for the various individual configuration spaces can be observed.

At the ultimate level of aggregation, an "average" ideal point representative of all subjects within a given group will be located within the group configuration space. Since the result of this technique will be a single ideal point representing the average of group preference judgments, the ranking of the stimuli in terms of predicted group preference will be entirely analogous to the procedures described above for the individual models. For investor groups an additional test to determine the correlation of predicted investment preference with investment behavior is possible; thus it will be hypothesized that the ranking of stocks according to their proximity to the group ideal point will be positively correlated with the ranking of their frequency of selection in the hypothetical portfolios created by group members.

This concludes the discussion of the procedures, data gathering and analysis techniques, and computer routines to be used in the evaluation of the hypotheses postulated in Chapter I. The ultimate objective of this research methodology is to evaluate the extent to which MDS techniques can be used to construct predictive models of investor behavior which are sufficiently generalizeable so that accurate forecasts of the actions of important groups of investors can be made. If the predictive validity of the models described above is found to be high, while at the same time (in tests of $H_4$) satisfactory "outside" statistical labels can be assigned to the perceptual dimensions of individual and group configuration spaces, major steps will have been taken toward the construction of models which not only reflect the investment behavior
of "real world" investors, but which also can be used in the selection of investment alternatives which can be expected to provide above-average investment returns.

Chapters IV and V will discuss in specific detail the results of the research methodology described in this chapter.
CHAPTER IV

EVALUATION OF HYPOTHESES 1, 2, AND 3

Chapter III discussed the various methodologies to be used in the evaluation of the hypotheses of this research. Chapter IV begins to describe in detail the results of the application of these programs and MDS-related techniques to the data gathered from the sixty-two initial and fifty-three follow-up questionnaires judged acceptable for inclusion in this research. Hypotheses 1, 2, and 3, which were designed to provide an overview of the ways in which both individuals and investor groups perceive relationships among investment alternatives, will be discussed in this chapter. Hypotheses 4 and 5, which are aimed at the detailing and evaluation of specific models of investment behavior, will be the subject of Chapter V.

H1: The configuration of the stimulus set will be represented by a space of low dimensionality (i.e., at most, three dimensions).

In the evaluation of H1, individual multidimensional scaling solutions in from one to five dimensions were obtained for each subject. This was accomplished by submitting each respondent's 1 x 55 row vector of similarity judgments between the fifty-five pairs of stocks on the initial questionnaire to Version 6MP of Kruskal's MDSCL, multidimensional scaling program. Three runs with different starting configurations were made for each individual. This provided protection against "local" optimal solutions and insured that configurations with the lowest possible stress values were obtained in each dimension. (It
should be noted that, in practically all cases, stress values were virtually identical across all three runs. That is, little "local" optimization was encountered).

Tables 2 - 5 show the minimum stress values obtained for the individual scaling configurations in one to five dimensions. Considering all individuals for the moment as members of a single respondent group, an initial evaluation of the perceptual patterns of all respondents in regard to the selected common stock stimuli can be obtained.

TABLE 2
STRESS vs DIMENSIONALITY
CHEMICAL ANALYSTS

<table>
<thead>
<tr>
<th>Respondents</th>
<th>Dimensions</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1</td>
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<tr>
<td>CA- 1</td>
<td>.214</td>
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<tr>
<td>CA- 2</td>
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<td></td>
<td></td>
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<tr>
<td>Cum % Below .10</td>
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<tr>
<td>PC-12</td>
<td>.289</td>
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<tr>
<td>Respondents</td>
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<tr>
<td>Cum Below .10</td>
<td>0</td>
</tr>
<tr>
<td>Cum % Below .10</td>
<td>0.0</td>
</tr>
</tbody>
</table>
First, it is apparent that a wide range of perceptual dimensionality exists among the sixty-three analysts and portfolio managers. A very few respondents achieved low stress values in only one dimension, while others required two, three, or in a few cases, four additional dimensions before obtaining good "fits" between their similarity judgments and the calculated configuration space.

Second, if the number of dimensions required to achieve "excellent" fits is observed (i.e., Kruskal "stress" value of .10 or less) the majority of respondents required a configuration space of more than two dimensions in order to accurately portray the manner in which they perceive similarities or differences among common stocks. Table 6 shows the number of individuals who attained stress values below .10 at each dimensional level. Only about one-fifth of the respondents could be represented adequately in configurations of two dimensions or less. The rest required configuration spaces of at least three dimensions before sufficiently low stress values were obtained to indicate a close correspondence between derived configuration interpoint distances and respondents' subjective similarity judgments. Over one-third of the respondents required at least four dimensions to achieve stress values below .10, while three respondents (5% of the total sample) required five dimensions. No respondent required more than five dimensions to obtain a stress value below .10.

A summary of the results obtained in the testing of \( H_1 \) is included in Figure 8, which shows the mean stress values for all sixty-three individual scaling configurations in spaces of one to five dimensions. Three dimensions are required to lower the average stress value below the .10 level defined as an "excellent" fit between similarity judgments and derived interpoint distances. This implies that the "average" respondent is utilizing at least three salient variables or dimensions in order to differentiate between common stock alternatives.
FIGURE 8
AVERAGE STRESS VALUE, BY DIMENSION
FOR ALL RESPONDENTS (62)
TABLE 6
TOTAL RESPONDENTS ATTAINING "EXCELLENT" FITS
(KRUSKAL STRESS BELOW 10%) AT EACH DIMENSION

<table>
<thead>
<tr>
<th>Dimension</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Below 10%</td>
<td>2</td>
<td>10</td>
<td>26</td>
<td>21</td>
<td>3</td>
</tr>
<tr>
<td>Cum Below 10%</td>
<td>2</td>
<td>12</td>
<td>38</td>
<td>59</td>
<td>62</td>
</tr>
<tr>
<td>Cum Per cent</td>
<td>3.2%</td>
<td>19.3%</td>
<td>56.7%</td>
<td>95.2%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

In summary, results to this point indicate that, for most individuals, the investment evaluation and selection process involves more than two (and, in many cases, more than three) salient variables or criteria. A corollary implication is that, in general, the twodimensional portfolio selection models described in normative portfolio literature may be inadequate as bases upon which to build accurate descriptive or predictive models of individual investment behavior.

Although the data generated in the evaluation of \( H_1 \) support the conclusion that individual perceptual dimensionality is higher than initially suspected or hypothesized, the final assessment of this question, and its implications for further research, will await the results of the separate investor group analyses performed below under \( H_2 \) and \( H_3 \). These evaluations will include initial attempts to define and quantify differences between analyst and portfolio manager groups as well as to examine the nature of investor perceptions within the separate respondent groups.
H₂: Significant differences exist between the perceptual patterns of various groups of market participants.

Although certain generalizations about investor perceptual patterns can be made from the examination of the aggregate data of H₁, significant additional information can be obtained from the study of data accumulated across each of the four investor groups identified in this research. From these results should come inferences concerning the manner in which (a) amounts of information, (b) the "investment context" in which portfolio selection decisions are made, and (c) the nature and degree of homogeneity among investment alternatives affect the perceptual points of view of important investor groups.

A: Amount of Information

Both the chemical analyst respondent group and the non-chemical analysts completed initial questionnaires based on a list of eleven chemical stocks. It is assumed that any major differences in perceptual patterns between these two analyst groups are attributable primarily to differences in familiarity with and amounts of information possessed which pertains to the chemical stock stimuli. It is desired to determine how the volume and kinds of additional information possessed by a "specialist" in chemical stocks changes his perceptual configuration from that of the non-chemical analyst.

Tables 2 and 3 summarize the stress values in spaces of one to five dimensions obtained from the individual scaling configurations of all members of the chemical analyst and non-chemical analyst groups, respectively. Within the chemical analyst group a high degree of homogeneity is observed, with by far the majority of respondents requiring configuration spaces of precisely three dimensions in order to obtain stress values below the level required for an "excellent" fit. The
non-chemical analyst group exhibits a much more diverse spread of dimensionalities. Furthermore, nearly one-half of the non-chemical analysts require four or more dimensions before stress values below .10 are obtained, compared to the only one chemical analyst (out of thirteen) requiring at least four dimensions.

The impression of a lower dimensionality among chemical analysts is supported by Figure 9, which shows the mean stress values in one to five dimensions from the individual scaling solutions of all individuals in the two analyst groups. The mean stress values for the chemical analyst group are consistently below those for the non-chemical group and drop below .10 in only three dimensions. The non-chemical analyst respondents require four dimensions before a mean stress value below .10 is attained.

An additional approach toward determining the degree of diversity between the points of view of the two analyst groups uses the Tucker-Messick "VIEWS" individual differences program. The 1 x 55 vectors of similarity judgments obtained from each individual were combined to form a single 32 x 55 matrix (13 chemical analysts, 19 non-chemical analysts). This data was submitted to the Tucker-Messick program which first calculated a 32 x 32 matrix of intersubject correlation coefficients, then performed a Q-type factor analysis on the correlation matrix. Table 7 shows the percentage of total variance accounted for by each of the first three principal components in Tucker-Messick analyses of various pairs of respondent groups. Also shown is the cumulative variance explained by the first three principal components.

---

FIGURE 9
AVERAGE STRESS VALUES, BY DIMENSION,
FOR CHEMICAL ANALYSTS AND
NON-CHEMICAL ANALYSTS

![Graph showing average stress values by dimension for chemical analysts and non-chemical analysts.](image-url)
### TABLE 7

**TUCKER-MESSICK; TWO GROUPS: % VARIATION EXPLAINED BY FIRST THREE PRINCIPAL COMPONENTS**

<table>
<thead>
<tr>
<th>Groups</th>
<th>Components</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st</td>
<td>2nd</td>
<td>3rd</td>
<td>Total 1st-3rd</td>
<td></td>
</tr>
<tr>
<td>Chem. An. vs. Non-Chem. An.</td>
<td>35.27</td>
<td>15.43</td>
<td>7.52</td>
<td>58.22</td>
<td></td>
</tr>
<tr>
<td>Chem. An. vs. Port. Man.-Chem.</td>
<td>32.21</td>
<td>22.97</td>
<td>6.23</td>
<td>61.41</td>
<td></td>
</tr>
<tr>
<td>Chem. An. vs. Port. Man.-Diverse</td>
<td>35.17</td>
<td>22.42</td>
<td>7.85</td>
<td>65.44</td>
<td></td>
</tr>
<tr>
<td>Non-Chem. An. vs. Port. Man.-Chem</td>
<td>34.92</td>
<td>9.47</td>
<td>6.13</td>
<td>52.52</td>
<td></td>
</tr>
<tr>
<td>Non-Chem. An. vs. Port. Man.-Diverse</td>
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<td>17.76</td>
<td>7.62</td>
<td>53.03</td>
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</tr>
<tr>
<td>All Analysts vs. Port. Man.-Chem.</td>
<td>33.47</td>
<td>15.05</td>
<td>7.02</td>
<td>55.54</td>
<td></td>
</tr>
</tbody>
</table>

It is noted that the Tucker-Messick results for the combined chemical analyst-non-chemical analyst matrix show that the first principal component accounts for an appreciable percentage (35% of total variance, with the second component explaining a relatively small amount (15%) compared to the first. The third and subsequent principal components account for substantially smaller proportions of total variance. It is concluded, therefore, that a single, dominant "point of view" exists among the combined analyst group, with a weaker secondary point of view also present. Remaining variation reflects only unsystematic individual perceptual differences.

Figure 10 shows a plot of the first two principal component "scores" derived from the Tucker-Messick application described above,
FIGURE 10

PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES, FROM TUCKER-MESSICK VIEWS PROGRAM, FOR CHEMICAL ANALYSTS AND NON-CHEMICAL ANALYSTS

□ = Non-Chemical Analysts
○ = Chemical Analysts
for all security analysts. As would be expected from the principal components analysis, no distinct division or separation between chemical analysts and non-chemical analysts is apparent. It does appear, however, that two clusters containing members of both analyst groups are visible and distinct, presumably corresponding to the dominant and secondary "points of view" identified from the variance data discussed earlier.

The Tucker-Messick information is confirmed and amplified by the Ward Hierarchical Clustering results highlighted in Figure 11. The $1 \times 55$ vectors of similarity judgments from all thirty-two individuals in both analyst groups were first standardized, then submitted to the Ward clustering and interpretive routines described in Chapter III. The output of this technique is a plot on the order of Figure 11, called a "phenogram." The horizontal axis (not shown) identifies the specific individuals included in the groups or clusters defined by the vertical dividing lines. The vertical axis represents the percent of total variation in the data as measured by the error sum of squares (E.S.S.). As successive clusters are identified, the distances between the corresponding horizontal lines indicate the extent to which additional "information" is obtained about the subjects being clustered. The objective of the Ward technique is to substantially improve the accuracy and understanding of intra-group evaluations (i.e., reduce E.S.S.) through the clustering of individuals into a manageable number of subgroups.

Figure 11 indicates that the optimum division of the combined analyst group into two clusters results in a 25 per cent reduction in E.S.S. Three groups achieve approximately a 50 per cent reduction, while the four-cluster level (not shown entirely) reduces E.S.S. by
FIGURE 11
WARD CLUSTERING RESULTS FOR SECURITY ANALYSTS
only another 10 per cent. Additional levels of clustering are not shown because (a) only minor reductions in E.S.S. are obtained, and (b) the number of different clusters becomes too numerous for efficient evaluation and comparison.

Of primary interest in this research is the degree to which clustering results are consistent with initial respondent group labels. These results will provide a measure of the significance of difference in perceptual patterns between the various analyst and portfolio manager groups.

Table 8 shows the composition (by analyst group) of the first two clusters of respondents defined by the Ward technique and shown in the phenogram of Figure 11. Cluster 1 on Figure 11 contained nineteen respondents, of which fifteen belonged to the non-chemical analyst group and four were chemical analysts. Cluster 2, on the other hand, was composed primarily of chemical analysts who represented nine of the thirteen individuals in this group. Although some cross-representation can be observed, it is apparent that clustering on the basis of the 1 x 55 vectors of similarity judgments results in calculated analyst groupings which tend to match the original "chemical analyst" and "non-chemical analyst" subject labels. The calculated chi-square statistic for the frequency distribution shown in Table 8 is 5.36, which is significant at the \( \alpha = .05 \) level.\(^2\) This indicates that the Ward Clustering program was successful in distinguishing between chemical analysts and non-chemical analysts on the basis of their similarity judgments.

---

TABLE 3
COMPOSITION OF FIRST TWO ANALYST CLUSTERS IDENTIFIED IN FIGURE 11

<table>
<thead>
<tr>
<th></th>
<th>Chem. Analysts</th>
<th>Non-Chem. Analysts</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1</td>
<td>4</td>
<td>15</td>
<td>19</td>
</tr>
<tr>
<td>Cluster 2</td>
<td>9</td>
<td>4</td>
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</tr>
<tr>
<td>Total</td>
<td>13</td>
<td>19</td>
<td>32</td>
</tr>
</tbody>
</table>

Finally, it can be seen that the results derived in this instance from the Tucker-Messick "VIEWS" program and the Ward Clustering Routine are mutually supportive. Both techniques imply the existence of two separate perceptual patterns among analysts surveyed in this research. Both techniques tend to link the two "points of view" with the two analyst groups surveyed; yet both methods indicate that this matching is not perfect and that a degree of overlap or confusion between the two groups is present. Along these lines, both the Ward technique and the Tucker-Messick (plot) show that four chemical analysts appear to exhibit perceptual patterns more in tune with the presumably less knowledgeable non-chemical analysts than with those of other members of the chemical analyst group.

In summary, it is concluded that the amount of information possessed by an individual concerning a set of common stock investment alternatives can affect the manner in which he perceives or distinguishes between the various investments. With both analyst groups completing chemical questionnaires, the multidimensional scaling configurations of the presumably more knowledgeable chemical analysts displayed consistently lower dimensionalities than those of the non-chemical analysts.
Furthermore, mean stress values for the chemical "specialists" were below those of the non-chemical analysts in all dimensions. Furthermore, attempts to re-create original analyst groups by clustering individuals on the basis of similarities in their perceptual data were largely successful.

To this point, however, the only concrete differences identified between the two analyst groups concern the number of dimensions required to characterize the perceptual patterns of each group. The "VIEWS" program and the Ward Clustering Routine indicate the significance of perceptual differences between groups, but offer little information concerning the precise nature of these differences. Beyond the assessment of perceptual dimensionality, additional discussions concerning the nature of differences between groups must await the evaluation of H4 when attempts will be made to provide specific labels to the axes of respondent group configuration spaces.

B. Investment Context

It is hypothesized that security analysts and portfolio managers differ in the manner in which they perceive similarities and differences among common stocks. This is a result of the varying objectives, constraints, and criteria which influence each group's security evaluations and investment decisions. In order to test this hypothesis, comparisons were made between the scaling results of the combined (chemical and non-chemical) security analyst group and those of the portfolio managers who completed initial questionnaires based on an identical (chemical) list of common stocks.

Table 4 shows the calculated stress values in spaces of one to five dimensions obtained from the individual multidimensional scaling
solutions of the fifteen portfolio managers who completed the "chemical" initial questionnaire. As is shown, spaces of at least three and, for seven of fifteen respondents, four dimensions were required to reduce the Kruskal stress measure below .10. Table 9 compares the results for the portfolio manager-chemical group with similar data from the security analyst groups discussed earlier. The perceptual dimensionalities of the portfolio manager respondents are seen to be similar to those of the non-chemical analysts. In both cases slightly over one-half of the group members obtained satisfactory fits in three dimensions or less, with another forty per cent of group members requiring an additional (fourth) dimension. Overall comparisons between the portfolio managers and the combined analyst group are rendered less meaningful because of the highly divergent dimensionalities between the two security analyst groups. As expected, the total analyst group exhibits a somewhat lower dimensionality than the PM-chemical group, as evidenced by the higher percentage of individuals (68% vs. 53%) requiring three dimensions or less to achieve Kruskal stress values below ten per cent.

Similar results are obtained when mean stress values from one to five dimensions are obtained for the individuals in the combined analyst groups and the PM-chem respondents. A plot of this data is shown in Figure 12. The strong degree of consistency between the perceptual dimensionalities of the portfolio managers and the non-chemical security analysts is easily observed, as well as the degree to which the chemical analysts differ from both groups. As with the non-chemical security analysts, the portfolio manager-chemical group required four dimensions before a mean stress value below .10 is obtained.
FIGURE 12
AVERAGE STRESS VALUES, BY DIMENSION, FOR SECURITIES ANALYSTS AND PORTFOLIO MANAGERS—CHEMICAL

Portfolio Managers—Chemical

Non-Chemical Analysts

Combined Security Analyst Group

Chemical Analysts

Average Stress vs. Dimension


<table>
<thead>
<tr>
<th>Group</th>
<th>Dimensions</th>
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<tr>
<td></td>
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<tr>
<td>Chem. Analysts</td>
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<tr>
<td>Cum %</td>
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<tr>
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<td>Cum %</td>
<td>(5.2)</td>
</tr>
<tr>
<td>Total Analysts</td>
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<tr>
<td>Cum %</td>
<td>(6.3)</td>
</tr>
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<td>Port. Man.-Chem.</td>
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<tr>
<td>Cum %</td>
<td>(0.0)</td>
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</tbody>
</table>

The results of the application of the Tucker-Messick "VIEWS" program to the 1 x 55 vectors of similarity judgments gathered from respondents in both analyst groups and the PM-chemical group are listed as "analysts vs. PM-chemical" in Table 7. With 33 per cent of the total variation in the data explained by the first principal component or "point of view" and 15 per cent by the second, we conclude that a single perceptual pattern is predominant among these subjects, with a relatively less important secondary point of view also present. This result is clarified, however, when the portfolio manager-chemical group is matched separately in a Tucker-Messick application with each security analyst group in turn. The "chemical analyst vs. portfolio manager-chemical" line shows a much more even balance between the first (32% of total variation) and second (23% of total variation) principal components, implying the presence of two distinct points of view. On the other hand, the
"non-chemical analysts vs. PM-chemical" results show a clearly dominant single point of view, which indicates that a close correspondence exists between the perceptual patterns of these two groups of market participants.

Figure 13 shows the plot of the first two principal component scores derived from the "analysts vs. PM-chemical" Tucker-Messick application discussed above. No distinct groupings are apparent, although the chemical analysts are generally contained in two minor clusters near the outer edge of this distribution of respondents, while the non-chem analysts and portfolio managers are thoroughly intermingled.

Finally, the 1 x 55 vectors of similarity judgments from all individuals in both analyst groups and the PM-chemical group were used as inputs to the Ward Clustering program. Based on results to this point, it was expected that the initial clustering outcome (for these subjects) would distinguish between chemical analysts on the one hand versus a larger group comprised of both non-chemical analysts and portfolio managers-chemical on the other. Figure 14 summarizes the Ward Clustering results for these groups. As is shown, the first division of the entire group into two separate clusters reduces the total error sum of squares by nearly one-half. The larger of the two clusters contains thirty-two individuals, of whom twenty-six are either non-chemical analysts or portfolio managers-chemical, and six were chemical analysts. In the second cluster containing fifteen subjects, seven are chemical analysts and the rest either non-chemical analysts or portfolio managers. The calculated chi-square statistic, which indicates the extent to which this frequency distribution can be assumed to represent a successful or significant ability to distinguish between chemical analysts and other respondents,
FIGURE 13
PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES, FROM TUCKER-MESSICK VIEWS PROGRAM, FOR SECURITY ANALYSTS AND PORTFOLIO MANAGERS-CHEMICAL

□ = Portfolio Managers-Chemical
○ = Non-Chemical Analysts
◆ = Chemical Analysts
WARD CLUSTERING RESULTS FOR SECURITY ANALYSTS AND PORTFOLIO MANAGERS-CHEMICAL
is 3.90. This value is significant at the $\alpha = 0.05$ level. There is no evidence that further clustering within the larger group could be viewed as identifying or distinguishing between non-chemical analysts and portfolio managers-chemical. Such attempts provided no statistically significant results.

In summary, any differences in perceptual patterns which may exist due to the differing nature of the investment "context" between security analysts and portfolio managers appear to be totally overshadowed or dominated by the effects of the "information" variable examined earlier. That is, no significant distinction can be made, either in terms of perceptual dimensionality or in terms of over-all patterns of investment evaluation between portfolio managers and security analysts whose areas of expertise do not include the common stocks used as stimuli. It is extremely difficult to evaluate which of the two "non-specialist" groups might be presumed to possess more information about the list of chemical common stocks, but both would certainly possess far less than the chemical analysts. It is this distinction which stands out most clearly in this initial examination of the perceptual patterns of various investor groups, and which will be considered in further detail during the evaluation of $H_4$.

C. Nature of the Stimulus Set

The objective of this section is to examine the manner in which variations in the set of investment alternatives being considered can influence the perceptual patterns of investors. The thirty portfolio managers who took part in this study were randomly assigned to one of two groups. One group of fifteen portfolio managers completed the "chemical" initial questionnaire, while the others completed the "diverse" initial questionnaire. It is hypothesized that differences in the stimulus sets
will result in significant differences in the perceptual patterns of the two portfolio manager groups.

Tables 4 and 5 list the stress values in spaces of from one to five dimensions obtained from the individual scaling configurations of the portfolio manager-chemical and portfolio manager-diverse group members. As noted earlier, configuration spaces of at least three or four dimensions were required to accommodate the similarity judgments of the portfolio manager-chemical group. For the diverse group, however, nearly one-half the respondents obtain "excellent" fits in two dimensions, with the remainder spread over three and four dimensions. It appears, therefore, that for a substantial portion of portfolio managers, increased diversity of the stimulus set may reduce the dimensions or number of variables by which investment alternatives are evaluated.

Figure 15 plots the mean stress values for spaces of one to five dimensions for the individuals in the two portfolio manager groups. The portfolio manager-diverse group exhibits consistently lower perceptual dimensionalities than the portfolio manager-chemical group. Furthermore, the "average" PM-chemical respondent required four dimensions to accurately portray his similarity judgments between pairs of chemical stocks, while the same result (i.e., Kruskal stress below .10) was achieved for the diverse list in only three dimensions. In summary, it appears that the homogeneous list of chemical stocks resulted in generally higher perceptual dimensionalities among portfolio managers than the randomly-selected diverse list of common stocks.

As expected, both the Tucker-Messick "VIEWS" technique and the Ward Clustering Routine reveal the existence of two distinct points of view or clusters within the portfolio manager group. These results
Figure 15

Average Stress Values, by Dimension, for Portfolio Managers

Portfolio Managers - Chemical

Excellent Fit

Portfolio Managers - Diverse

Average Stress

Dimension
merely confirm the usefulness and discriminative ability of the techniques themselves, however, since the two sets of 1 x 55 similarity vectors which were used as input for these programs were derived from two different stimuli sets and were, therefore, essentially independent of one another. Nevertheless, the results of the application of both techniques to the portfolio manager data will be included and discussed briefly for illustrative purposes.

The Tucker-Messick results shown in Table 7 clearly reveal the effects of the inclusion of the PM-diverse group of respondents with data from the other investor groups whose judgments are based on a different list of common stocks. Whenever the PM-diverse individuals are paired with one of the other investor groups, both the first and second principal components account for a significant percentage of the total variation in the data. This result implies that two separate and distinct viewpoints are prevalent in the data, which is to be expected based on the differing stimulus sets between the portfolio manager-diverse individuals and any of the other respondent groups. Figure 16 shows the plot of the first two principal component "scores" from the Tucker-Messick routine as applied to the judgmental data from the two portfolio manager groups. The distinctive clustering of these two groups is precisely the result to be expected on the basis of the differing stimulus sets used by the respondents. Similar results were obtained when the PM-diverse individuals were paired with respondents from either of the two security analyst groups.

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3 Two stocks, Monsanto and Minnesota Mining & Manufacturing, were common to both the chemical and diverse lists. This means that one paired comparison (out of fifty-five) was common to all portfolio manager data sets.
FIGURE 16

PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES, FROM TUCKER-MESSICK VIEWS PROGRAM FOR PORTFOLIO MANAGERS

○ = Portfolio Managers—Chemical
□ = Portfolio Managers—Diverse
The Ward Clustering Routine was equally successful in confirming the distinction between the PM-diverse and PM-chemical respondents. Figure 17 shows that the first division of the entire group of thirty portfolio managers into two separate clusters reduces the error sum of squares by about two-thirds, a highly significant result. Furthermore, the membership in the two clusters corresponds exactly to the original portfolio manager-diverse and portfolio manager-chemical groups.

The conclusions of this section have been limited to the finding that the increased diversity of the stimulus set tended to result in a lower perceptual dimensionality among portfolio managers than that observed for the more homogeneous list of chemical common stocks. The results of the Tucker-Messick "VIEWS" and Ward Clustering Routine applications to the combined portfolio manager group data merely confirms the assumed "significance" of the differences in perceptual viewpoint between the two groups, rather than providing any new information as to the nature of these differences. As noted previously, the later attempts to define or label the perceptual dimensions of the various group configuration spaces will provide additional information on the effects of the variables considered in the evaluation of $H_2$.

$H_3$: Significant "clusters" of individuals within the larger sample groups can be identified as having similar perceptual judgments or patterns in relation to the stimuli set.

The previous hypothesis was concerned with examining the ways in which perceptual patterns differ between the various investor groups. $H_3$ examines the extent to which the respondent groups sampled in this research can be considered "homogeneous" in terms of the manner in which they perceive similarities and differences among common stocks. Both the Tucker-Messick "VIEWS" program and the Ward Hierarchical Clustering routine will be used to examine the four original investor groups for significant subgroups or "clusters" of individuals with distinct "points of view."
FIGURE 17
WARD CLUSTERING RESULTS
FOR PORTFOLIO MANAGERS

100
80
60
40
20

15
15
12
8
3
7
8
A. Chemical Security Analysts

Table 10 shows the results of the Tucker-Messick "VIEWS" program as applied to the 1 x 55 vectors of similarity judgments from all members of the various respondent groups. As is shown, for the chemical analyst group the first principal component or point of view explained over 56 per cent of the total variation in the judgmental data. This is a highly significant result, especially when compared to the 14 per cent and 7 per cent of total data variation explained by the second and third principal components, respectively. The implication of this data is that, among the chemical analyst respondents, a single perceptual pattern or point of view dominates all others. Furthermore, since 77 per cent of the total variation is accounted for by the first three principal components, it can be assumed that idiosyncratic (individual) contributions to total variation are small, revealing a high degree of homogeneity among the members of the chemical analyst group.

<table>
<thead>
<tr>
<th>Group</th>
<th>1st (%)</th>
<th>2nd (%)</th>
<th>3rd (%)</th>
<th>Total 1st-3rd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemical Analysts</td>
<td>56.31</td>
<td>13.80</td>
<td>6.86</td>
<td>76.97</td>
</tr>
<tr>
<td>Non-Chemical Analysts</td>
<td>42.49</td>
<td>10.76</td>
<td>9.98</td>
<td>63.23</td>
</tr>
<tr>
<td>Port. Man.-Chemical</td>
<td>41.78</td>
<td>12.46</td>
<td>7.70</td>
<td>61.94</td>
</tr>
<tr>
<td>Port. Man.-Diverse</td>
<td>55.84</td>
<td>9.73</td>
<td>7.32</td>
<td>72.89</td>
</tr>
</tbody>
</table>
Figure 18 shows the plot of the subject "scores" on the first two principal components from the Tucker-Messick analysis. Some minor clustering among two or three individuals can be identified, but to attempt any further analysis based on these small groups of individuals would offer little additional useful information in the development of generalizable investor models. Instead, based on the earlier Tucker-Messick results discussed above, it is concluded that the perceptual viewpoints of the individual chemical analysts are sufficiently similar to allow the construction of a single configuration space which can be assumed to represent adequately the perceptual patterns of the entire group of chemical analysts.

The conclusions derived thus far are confirmed by the Ward Clustering Routine results, shown in Figure 19, as derived from the similarities data gathered from the chemical analyst respondents. As is seen, initial groupings of chemical analysts reduce the error sum of squares by only minor amounts, implying that treatment of the entire group as a homogeneous cluster of individuals sacrifices little in the way of additional information. In other words, the evaluative accuracy of further analysis would not be improved significantly by the clustering of individuals into a reasonable number of subgroups.

In summary, no significant subgroups of the chemical analyst respondents with distinctive points of view have been identified. For this reason, subsequent testing and analyses may be performed on a single configuration space constructed for the entire chemical analyst group rather than on the individual spaces calculated heretofore for each respondent.
FIGURE 18

PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES,
FROM TUCKER-MESSICK VIEWS PROGRAM
FOR CHEMICAL ANALYST GROUP
FIGURE 15
WARD CLUSTERING RESULTS FOR CHEMICAL ANALYST GROUP
Non-Chemical Analysts

Table 10 shows that, while not as dominant as in the chemical analyst group, the first principal component or point of view in the non-chemical analyst group is by far the most prominent, accounting for over 42 per cent of total variation in the data. The second and third principal components each explain only about 10 per cent of the total variance. The first three principal components total approximately 63 per cent of the over-all data variation; the remainder is due to idiosyncratic variation which implies that the perceptual homogeneity of the non-chemical analyst group is below that of the chemical analysts. Nevertheless, we conclude that a single dominant point of view represented by the first principal component exists, coupled with a variety of individual dimensions which are not shared by enough non-chemical analysts to be explained on grounds other than error variance.

Figure 20 illustrates the plot of the first two principal component scores for each analyst. As expected, no distinct clustering of the respondents is apparent, although smaller groupings of three or four individuals may be discerned.

Finally, Figure 21 shows the results of the Ward Clustering Routine application to the $1 \times 55$ vectors of similarities judgments gathered from the non-chemical analyst respondents. As is shown, initial respondent clusters reduce the error sum of squares by only small amounts, thus negating the potential for significantly improved accuracy through the evaluation of the perceptual patterns of smaller "subgroups" of respondents.

In summary, individuals within the non-chemical analyst group will be considered sufficiently homogeneous to allow the construction of a single configuration space to represent the perceptual viewpoints of the entire respondent group.
FIGURE 20

PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES, FROM TUCKER-MESSICK VIEWS PROGRAM, FOR NON-CHEMICAL ANALYST GROUP.
FIGURE 21
WARD CLUSTERING RESULTS FOR
NON-CHEMICAL ANALYST GROUP
Portfolio Manager-Chemical

Table 10 indicates that, for the portfolio manager-chemical group of respondents, the first principal component or point of view accounts for about 42 per cent of total variance in the data, as opposed to 12 per cent for the second point of view and 8 per cent for the third. As with the previous two analyst groups, these results reveal the pre-dominance of a single perceptual pattern among the portfolio manager-chemical individuals, with individual deviations from this dominant pattern accounting for the remaining judgmental variation. Table 10 also shows that the first three principal components account for only about 62 per cent of total variance, indicating that the portfolio manager-chemical group exhibits the greatest amount of idiosyncratic variation and, therefore, the least degree of over-all homogeneity of any of the four respondent groups surveyed in this research.

Figure 22 shows a plot of the first two principal component scores for each individual derived from the Tucker-Messick results. The general dispersion of the "individual points" confirms the earlier conclusion that the portfolio manager-chemical group contains no significant subgroups or clusters of individuals with distinctive points of view.

Finally, the Ward Clustering results on the 1 x 55 individual similarity vectors (shown in Figure 23) reveal that the error sum of squares function is reduced by about 40 per cent for the first stage of clustering and by only small amounts for additional grouping levels. The E.S.S. reduction, considered in conjunction with the Tucker-Messick results discussed earlier, is not considered sufficient to warrant the separation of the portfolio manager-chemical group into two distinct subgroups for further analysis. Thus, as with the two security analyst groups discussed previously, subsequent analyses will be performed on a single configuration space constructed to summarize the perceptual viewpoints of all portfolio managers who responded to the chemical questionnaires.
FIGURE 22

PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES, FROM TUCKER-MESSICK VIEWS PROGRAM, FOR PORTFOLIO MANAGER-CHEMICAL GROUP
FIGURE 23
WARD CLUSTERING RESULTS FOR PORTFOLIO
MANAGER-CHEMICAL GROUP

100
80
% E.S.S.
60
40

10
5
3
3
4
4
Portfolio Managers-Diverse

Table 10 shows that the first principal component accounted for nearly 56 per cent of the total variation in the portfolio manager-diverse data, compared to 10 per cent for the second and 7 per cent for the third point of view. This data strongly indicates the dominance of a single perceptual pattern among the PM-diverse individuals, with idiosyncratic perceptual viewpoints accounting for the remaining variation. Furthermore, with 73 per cent of total variation accounted for by the first three principal components, the portfolio manager-diverse group exhibits a degree of over-all perceptual homogeneity second only to that of the chemical analysts. As expected, the plot of the first two principal component scores, shown in Figure 24, gives no indication of the existence of significant subgroups of individuals with distinctive perceptual patterns.

Finally, Figure 25 highlights the Ward Clustering Routine results as calculated from the similarities data of the PM-diverse respondents. As is shown the first level of clustering, which reduces E.S.S. by roughly 35 per cent places only two individuals in the second group. Subsequent clustering levels do not significantly further reduce the error sum of squares. These results, combined with the Tucker-Messick data discussed earlier, lead to the conclusion that no substantial improvement in understanding would be achieved by performing subsequent analyses on smaller subgroups of the larger PM-diverse subject group.

SUMMARY

As noted previously, Chapter IV was concerned primarily with determining important characteristics of the nature of individual perceptual patterns, as well as determining the extent to which perceptual viewpoints
FIGURE 24

PLOT OF FIRST TWO PRINCIPAL COMPONENT SCORES, FROM TUCKER-MESSICK VIEWS PROGRAM, FOR PORTFOLIO MANAGER-DIVERSE GROUP
FIGURE 25
WARD CLUSTERING RESULTS FOR PORTFOLIO
MANAGER-DIVERSE GROUP
differ both within and between important market groups. A summary of the important results of Chapter IV is as follows:

1. The majority of respondents surveyed (81%) required more than two dimensions in order to portray accurately the manner in which they perceived similarities or differences among a list of common stock investment alternatives. Either three or four dimensions were sufficient for roughly three-fourths of the individuals surveyed.

2. The amount of information possessed by an investor concerning a set of potential investments significantly influences the manner in which he perceives similarities or differences among the securities. "Specialist" and "non-specialist" security analysts differed markedly in both perceptual dimensionality and in over-all patterns of evaluation in the judging of similarities between identical pairs of common stocks.

3. No significant differences in perceptual patterns were identified between "non-specialist" security analysts and portfolio managers.

4. Increased diversity of the stimulus set (in terms of common industry labels) tended to decrease the dimensionality of perceptual patterns among portfolio managers. 4

5. The attempts to identify significant clusters within the larger investor groups with distinctive perceptual patterns or "points of view" were unsuccessful. Individual perceptual patterns within the various security analyst and portfolio manager groups studied were determined to be sufficiently homogeneous to allow the construction of single "group" configuration spaces of all group members.

4 It is possible, however, that an interaction occurred in this instance between those effects caused by the nature (diversity) of the stimulus set, and effects caused by the "information" variable of par. 2. That is, since the stocks contained in the "diverse" list were all large, institutional favorites, it is possible that the high degree of knowledge and "familiarity" of these stocks among the portfolio managers was sufficiently greater than that pertaining to the "homogeneous" list to obscure or override any effects caused by the "homogeneity" of the stimulus set itself. Conclusive evidence in this area must await experimental designs constructed specifically to address this question.
Finally, as noted earlier, the efforts in Chapter V to define or "label" the perceptual dimensions of the various "group" configuration spaces will provide additional information on the effects of each of the variables discussed above as well as in general about the ways in which investment decisions are made.
CHAPTER V

EVALUATION OF HYPOTHESES 4 AND 5

The scaling results discussed in the previous chapter in the evaluation of hypotheses 1, 2, and 3 provide a broad overview and comparison of the perceptual patterns of security analysts and portfolio managers under varying information levels and stimulus sets. Of special importance to the discussion and analysis of $H_4$ below was the determination that the points of view of individuals within each of the four respondent groups exhibited a significant degree of homogeneity. This fact allows the construction of single configuration spaces which can be assumed to represent, with substantial accuracy, the perceptual viewpoints of all group members. These "group" configuration spaces will be closely examined under the discussion of $H_4$ in the attempt to identify or "label" the dimensions by which important investor groups distinguish between common stock investment alternatives. After such attempts to formulate descriptive models of investment behavior are completed, individual group preference data will be introduced in the attempt to construct and evaluate models of both individual and group investment actions. This will be the subject of later discussions presented below under $H_5$.

$H_4$: Assuming stimulus configurations are generated containing a minimum of two dimensions, both a "return" and a "risk" axis will be identified.

For each of the four investor groups studied in this research, the analytical procedure under $H_4$ will be the same. First, a "group" configuration space will be defined by submitting the basic similarity-
dissimilarity judgments from all respondents in a given group to the Carroll-Chang INDSCAL computer program. As noted earlier, the INDSCAL technique constructs a single, "shared" perceptual space for a group of subjects in as many dimensions as desired. Furthermore, the axes of the group space, unlike those of normal multidimensional routines such as MD-SCAL, are uniquely determined. 

After a single configuration space is defined for each respondent group, the "max r" procedure, as contained in the PROFIT computer program developed by Carroll and Chang, will be used to locate the various "property vectors" in the configuration space. The ultimate objective is to associate the axes or dimensions of the group space with one or a group of property vectors derived from either the respondents' subjective ratings of each stock on a variety of investment attributes, or from objectively measured return, risk, and growth data calculated for each security. As noted in Chapter III, initial labeling attempts will utilize only the subjectively determined property vectors obtained from respondents' estimates of the characteristics or nature of the stimulus set. Subsequent labeling using objectively calculated property vectors will provide an insight into which statistical variables are most closely associated with investor judgmental and evaluative patterns, and which, therefore, are most useful in the construction of accurate descriptive investor behavior models.

1 J. Douglas Carroll and Jih-Jie Chang, "How to use INDSCAL."


3 Jih-Jie Chang and J. Douglas Carroll, "How to use PROFIT."

4 See discussion in Chapter III and Appendix E.
A: Chemical Analyists

The basic inputs to the Carroll-Chang INDSCAL computer program are the 1 x 55 vectors of similarity judgments gathered from each respondent via the initial questionnaire. The INDSCAL technique utilizes this data to construct a single "shared" configuration for all members of the respondent group, recognizing idiosyncratic variations to this shared space by the differing "weights" assigned by subjects to the dimensions of the group space.

As noted earlier, INDSCAL will construct the "shared" space in as many dimensions as are desired. The program also calculates, for each level of dimensionality, the "average subject correlation coefficient," which is a measure of the goodness of fit between the INDSCAL shared space results and the original individual judgmental data. Table 11 shows, by dimension, the average correlation coefficients for the chemical analyst INDSCAL computations. Since in the analysis of $H_2$ it was shown that most chemical analysts exhibit three-dimensional configuration spaces, and since the average subject correlation coefficient in the INDSCAL analysis does not increase appreciably beyond the third dimension, the INDSCAL shared space in three dimensions will be used for subsequent axis labeling efforts for the chemical analyst group.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.641</td>
</tr>
<tr>
<td>2</td>
<td>.742</td>
</tr>
<tr>
<td>3</td>
<td>.775</td>
</tr>
<tr>
<td>4</td>
<td>.802</td>
</tr>
<tr>
<td>5</td>
<td>.823</td>
</tr>
</tbody>
</table>

TABLE 11
CHEMICAL ANALYSTS' INDSCAL AVERAGE SUBJECT CORRELATION COEFFICIENTS
Figures 26, 27, and 28 portray graphically the three-dimensional INDSCAL results for the chemical analyst respondents. As with the earlier MDSCAL scaling efforts, multiple runs were made to insure against local optimization problems. Preliminary attempts to identify axis labels from known characteristics of the "outliers" on Figures 26, 27, and 28 appear useless. In general, Union Carbide, 3M, Commercial Solvents, and Celanese are found at the extremes of the shared space dimensions. However, because of the generally homogeneous nature of the chemical list of companies (at least to an individual who is not intimately familiar with the chemical industry in all its facets) few, if any, tentative conclusions can be drawn from this data in terms of axis interpretation.

Fortunately, an additional tool in the form of the Carroll-Chang PROFIT program is available in order to assist in providing labels to the dimensions of a given configuration space. As noted earlier, initial axis labeling efforts will utilize property vectors derived from the individuals' subjective ratings of each security on a variety of potentially important investment attributes. A list of these variables is shown in Table 12. These ratings were averaged across all chemical analysts who completed the follow-up questionnaire in order to provide the property vectors to be submitted, along with the coordinates of the three-dimensional chemical analyst group space, to the Carroll-Chang PROFIT program. This routine finds, for each property vector, the direction vector in the configuration space located such that stimulus point projections onto the direction vector are maximally correlated with the property vector's scale values for each of the stimuli. The program also calculates the correlation coefficient between stimulus point projections onto a given direction vector and the stimulus scale values on the corresponding property vector. With eleven stimulus points on each property
FIGURE 26

INDSCAL CHEMICAL ANALYST GROUP CONFIGURATION SPACE (DIMENSION I VS. II)
FIGURE 27
INDSCAL CHEMICAL ANALYST GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 26

INDSCAL CHEMICAL ANALYST GROUP CONFIGURATION SPACE (DIMENSION I VS. III)

Dim III

- 3M
- Dow
- Union Carb.
- DuPont
- Monsanto
- Celanese
- PPG
- Comm. Solv.
- Koppers
- Allied Chem.
vector and corresponding direction vector, a correlation coefficient (r) greater than .62 or less than -.62 is significant at the $\alpha = .05$ level. Any direction vector whose computed correlation coefficient does not have an absolute value above .62 will not be considered as a potential axis label.

**TABLE 12**

**SUBJECTIVELY ESTIMATED PROPERTY VECTORS USED IN PROFIT AXIS LABELING CALCULATIONS**

<table>
<thead>
<tr>
<th>Vector No.</th>
<th>Variable Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Expected 3-5 year growth in earnings per share</td>
</tr>
<tr>
<td>2</td>
<td>Expected 3-5 year total returns (dividends plus price appreciation)</td>
</tr>
<tr>
<td>3</td>
<td>Expected 3-5 year investment risk</td>
</tr>
<tr>
<td>4</td>
<td>Expected 3-5 year dividend yield</td>
</tr>
<tr>
<td>5</td>
<td>Liquidity (ability to sell large blocks quickly, near current market)</td>
</tr>
<tr>
<td>6</td>
<td>Expected 12 month growth in earnings per share</td>
</tr>
<tr>
<td>7</td>
<td>Expected 12 month total return (dividends plus price appreciation)</td>
</tr>
<tr>
<td>8</td>
<td>Expected 12 month investment risk</td>
</tr>
<tr>
<td>9</td>
<td>Expected 12 month dividend yield</td>
</tr>
<tr>
<td>10</td>
<td>Quality of management</td>
</tr>
</tbody>
</table>

Figures 29, 30, and 31 illustrate the results of the PROFIT axis labeling program application to the chemical analyst group configuration space and property vectors derived from these same individuals' subjective ratings of the chemical stocks on several potentially important factors.

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5Sidney Siegel, Nonparametric Statistics for the Behavioral Sciences.
FIGURE 29

CHEMICAL ANALYST GROUP SPACE, SUBJECTIVE PROPERTY VECTORS, DIMENSION I VS. II
FIGURE 30

CHEMICAL ANALYST GROUP SPACE, SUBJECTIVE PROPERTY VECTORS, DIMENSION II VS. III
FIGURE 31

CHEMICAL ANALYST GROUP SPACE, SUBJECTIVE PROPERTY VECTORS, DIMENSION I VS. III
investment attributes. The numbers at the apex of each vector correspond to those shown in the Table 12 list of investment attributes. The length of the direction vectors shown in these (and all subsequent) axis labeling charts are directly related to the calculated $r$ value between the stimulus projections onto the direction vector and the original property vector scale values. The optimal results, then, would be to observe a very long direction vector (indicating high correlation) which is almost co-linear with one of the dimensions of the group configuration space.

As shown in Figures 29, 30, and 31, direction vectors for all of the ten attributes by which chemical analysts subjectively ranked the common stock stimuli were located in the group configuration spaces with sufficiently high correlation coefficients to be considered significant. It is also apparent that major groupings of property vectors are observed in the space and that a majority of the vectors fall between configuration axes. The grouping of property vectors occurs when a high degree of correlation exists between (estimated or calculated) security scale values on several different potential axis labels or investment attributes. In this specific context, the grouping implies that analysts tended to maintain their patterns of ranking across several of the investment attributes, rather than substantially modifying their rank orderings from one attribute to another. Since the group space dimensions themselves are assumed to be uniquely located, the fact that many property vectors fall between the axes implies that these attributes are not fundamental to investment evaluation, or that they represent combinations of more basic investment variables which, if properly identified, would be located nearly colinearly with the configuration axes.
Nevertheless, for the chemical analyst individuals, certain initial axis labeling conclusions can be drawn. First, dimension III stands out clearly as an "expected dividend yield" axis. Property vectors 4 and 9, which deal with dividend yield over both short and long-term time periods, are seen to be nearly colinear with dimension III in Figures 30 and 31, yet lie between dimensions I and II in Figure 29. The calculated r values for property vectors 4 and 9 are .74 and .71, respectively.

In addition, property vector 5, "liquidity," appears to be an appropriate label for dimension I. Figure 29 illustrates that vector 5 lies much closer to dimension I than dimension II, while Figures 30 and 31 show that this vector has a very small axis III component. The calculated r value for the "liquidity" vector is .90.

Determining a suitable label for dimension II from the subjective data gathered from the chemical analysts appears difficult. Property vector 3, "long-term investment risk" appears to be the only plausible candidate. Figures 30 and 31 show that this vector has very little dimension III component, but Figure 29 indicates that this "risk" vector is only slightly more highly correlated with dimension II than with dimension I. The over-all r value for vector 3 is .93, which is quite high. It appears best, at this stage, to hold the assignment of a label for dimension II in abeyance pending the additional analysis of the objectively calculated property vectors discussed below.

To this point, then, tentative labels have been assigned to two of the three dimensions of the chemical analyst group space. Dimension I appears to be highly correlated with analysts' subjective rankings of chemical stocks by degree of liquidity, while dimension III has been aligned with investor estimates of the potential dividend yield from the same list of chemical stocks. Only dimension II remains undefined, with
some indication present that this axis might be evaluated in terms of investment risk.

As discussed previously in Chapter III, in addition to being rated subjectively by each respondent, each stock in the chemical and diverse lists was objectively measured in terms of a variety of statistical risk, return, or company financial variables. A list of these "statistical" property vectors to be used in further axis labeling efforts is shown in Table 13. This list is divided into measures derived from (a) Forbes magazine's Annual Report on American Industry, and (b) the Harvey RISK program applied to historical stock price data from the members of the stimulus set.

Figures 32, 33 and 34 illustrate the axis labeling results for the objectively measured property vectors. It should be noted that not every property vector on the list in Table 13 achieved a sufficiently high r value when located in the group space to be considered significant. The direction vectors for these variables are not shown. Numbers at the end of each direction vector refer to the numerical listing of property vectors in Table 13.

Evaluation of the axis labeling results in Figures 32, 33, and 34 reveal some interesting results. First, property vector 21, five-year mean absolute deviation of returns, appears to be the only candidate as a potential label for dimension I. This vector is not strongly correlated with the other risk vectors in the Figures (vectors 16, 18, 19, and 20) and has an r value of .76, which is slightly higher than the r value for the liquidity property vector (.74) from which dimension I was initially labeled in an earlier discussion. The correlation between

TABLE 13
OBJECTIVELY CALCULATED PROPERTY VECTORS FOR USE IN PROFIT AXIS LABELING CALCULATIONS

<table>
<thead>
<tr>
<th>Vector Number</th>
<th>Variable Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Five-year average return on equity</td>
</tr>
<tr>
<td>2</td>
<td>Five-year average return on total capital</td>
</tr>
<tr>
<td>3</td>
<td>Five-year average annual sales growth</td>
</tr>
<tr>
<td>4</td>
<td>Five-year average annual earnings per share growth</td>
</tr>
<tr>
<td>5</td>
<td>Total five-year stock price growth</td>
</tr>
<tr>
<td></td>
<td><strong>A: FORBES DATA</strong></td>
</tr>
<tr>
<td>6</td>
<td>One-year arithmetic average monthly return</td>
</tr>
<tr>
<td>7</td>
<td>One-year geometric mean monthly return</td>
</tr>
<tr>
<td>8</td>
<td>Five-year arithmetic average monthly return</td>
</tr>
<tr>
<td>9</td>
<td>Five-year geometric mean monthly return</td>
</tr>
<tr>
<td>10</td>
<td>One-year standard deviation of monthly return</td>
</tr>
<tr>
<td>11</td>
<td>One-year coefficient of variation of monthly return</td>
</tr>
<tr>
<td>12</td>
<td>One-year semi-standard deviation of monthly return</td>
</tr>
<tr>
<td>13</td>
<td>One-year modified quadratic mean monthly return</td>
</tr>
<tr>
<td>14</td>
<td>One-year log deviation of monthly return</td>
</tr>
<tr>
<td>15</td>
<td>One-year mean absolute deviation of monthly return</td>
</tr>
<tr>
<td>16</td>
<td>Five-year standard deviation of monthly return</td>
</tr>
<tr>
<td>17</td>
<td>Five-year coefficient of variation of monthly return</td>
</tr>
<tr>
<td>18</td>
<td>Five-year semi-standard deviation of monthly return</td>
</tr>
<tr>
<td>19</td>
<td>Five-year modified quadratic mean monthly return</td>
</tr>
<tr>
<td>20</td>
<td>Five-year log deviation of monthly return</td>
</tr>
<tr>
<td>21</td>
<td>Five-year mean absolute deviation of returns</td>
</tr>
<tr>
<td></td>
<td><strong>B: STOCK PRICE DATA</strong></td>
</tr>
</tbody>
</table>
FIGURE 32

CHEMICAL ANALYST GROUP SPACE, OBJECTIVE PROPERTY VECTORS, DIMENSION I VS. II
FIGURE 33

OBJECTIVE PROPERTY VECTORS, CHEMICAL ANALYST
GROUP SPACE, DIMENSION II VS. III
FIGURE 34

OBJECTIVE PROPERTY VECTORS, CHEMICAL ANALYST
GROUP SPACE, DIMENSION I VS. III
the liquidity property vector scale values and those of the mean absolute deviation property vector is .73, which is statistically significant. It appears, then, that either the subjectively estimated attribute of liquidity or the objectively measured five-year mean absolute deviation of returns provides a suitable label for dimension I of the chemical analyst group space.

Turning to dimension II, it appears that, once again, no precise definition of this axis is available. As in the earlier discussion of subjective labels, several of the objectively measured risk variables (vectors 16, 18, 19, and 20) are tending to align themselves with dimension II. It is also apparent, however, that a slight rotation of dimension II would be required before a close alignment with the risk-oriented property vectors could be achieved. In summary, it is felt that dimension II probably represents the influence of the risk variable in the chemical analysts' perceptions of the common stock stimuli. However, a specific subjectively estimated or statistically measured "label" can not be applied to this axis, either because (a) the precise property vector required to align with and thus define this axis was not identified and included in either the follow-up questionnaire or the objective calculations of potential axis labels, or (b) because the INDSCAL calculation of the chemical analyst group space was not sufficiently accurate in the locating of configuration dimensions to correspond precisely to the salient perceptual variables of the chemical analyst respondents.

Dimension III, identified as an "expected dividend" axis in the evaluation of the subjective property vectors, appears to have no close statistical counterpart in the objective measures proposed as potential dimension labels. Only property vector 3, "five-year sales growth," appears to have sizeable dimension III component. However, its
relatively low r value (.69) and appreciable dimension II component (shown in Figure 33) substantially reduce the "five-year sales growth" property vector's usefulness as a statistical surrogate for the subjective label applied to dimension III.

In summary, generally mixed results are observed in the attempt to "label" the axes of the three-dimensional chemical analyst group configuration space. Using both subjectively estimated and objectively calculated property vectors as potential axis labels, both a return axis (dimension III-expected dividend yield) and a risk axis (dimension II) can be tentatively identified. Dimension I appears to correspond most closely to analysts' estimates of investment "liquidity." On the other hand, satisfactory statistical labels were defined only for dimension I, with no statistical property vectors achieving really satisfactory fits with either dimension II or III. Thus, although a degree of insight into the perceptual viewpoints of chemical analysts has been attained, the ultimate objective of this section, which is the construction of an accurate descriptive model of chemical analysts perceptual patterns using axes with objectively quantifiable labels, has not been achieved.

8: Non-Chemical Analysts

The 1 x 55 vectors of similarity judgments gathered from the non-chemical analyst respondents were submitted to the Carroll-Chang INDSCAL program in order to obtain the group configuration space. Table 14 shows the calculated "average subject correlation coefficient" for spaces of varying dimensions. Beyond configuration spaces of three dimensions, only minor increases in average subject correlation coefficient are achieved. Thus the non-chemical analyst group space in three dimensions will be used for subsequent axis labeling efforts and further analysis.
TABLE 14

NON-CHEMICAL ANALYSTS' INDSCAL AVERAGE
SUBJECT CORRELATION COEFFICIENTS

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.52</td>
</tr>
<tr>
<td>2</td>
<td>.61</td>
</tr>
<tr>
<td>3</td>
<td>.67</td>
</tr>
<tr>
<td>4</td>
<td>.71</td>
</tr>
<tr>
<td>5</td>
<td>.74</td>
</tr>
</tbody>
</table>

Figures 35, 36, and 37 illustrate the three-dimensional shared space configuration for the non-chemical security analysts. As before, few, if any, conclusions regarding dimensional interpretation can be made from a visual examination of the group configuration space. Although securities located at dimensional extremes (3M, Commercial Solvents, and Celanese) are largely the same for the non-chemical respondents as for the chemical analysts, the homogeneous nature of the stimulus set precludes any definitive conclusions about axis labels until the PROFIT calculations are thoroughly analyzed.

Figures 38, 39, and 40 illustrate the results of the PROFIT axis labeling program application to the non-chemical analyst group configuration space and the subjective set of property vectors derived from these analysts' ratings of the eleven chemical stocks on the investment attributes listed in the follow-up questionnaire. As before, direction vector identification numbers correspond to the numbers shown in Table 12.
FIGURE 35

INDSCAL NON-CHEMICAL ANALYST GROUP CONFIGURATION SPACE (DIMENSION I VS. II)
FIGURE 36
INDSCAL NON-CHEMICAL ANALYST GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 37
INDSCAL NON-CHEMICAL ANALYSTS GROUP CONFIGURATION SPACE (DIMENSION I VS. III)

Dim III

Monsanto

Celanese

Dupont

Allied Chem.

Dow

PPG

Union Carb.

Comm. Solv.

Diam. Sham.

Koppers

3M
FIGURE 38
SUBJECTIVE PROPERTY VECTORS, NON-CHEMICAL ANALYSTS
GROUP CONFIGURATION SPACE (DIMENSION I VS. II)
FIGURE 39

SUBJECTIVE PROPERTY VECTORS, NON-CHEMICAL ANALYSTS
GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 46

SUBJECTIVE PROPERTY VECTORS, NON-CHEMICAL ANALYSTS
GROUP CONFIGURATION SPACE (DIMENSION I VS. III)
Examination of the axis labeling results shows that only seven of the ten potential axis labels listed in Table 12 achieved sufficiently good fits in the non-chemical analyst group space (i.e., correlation coefficients > .60) to be considered further. Of these, only property vector 4, "expected 3-5 year dividend yield," appears to result in a clear and distinctive axis interpretation. Thus, as with the chemical analyst group, the non-chemical analysts appear to utilize expectations of long-term dividend yield as a salient attribute (dimension III) in their evaluations of similarities and differences among chemical stocks.

Labels for the other two dimensions are not nearly as evident. Evaluations of the chemical stocks on the remaining attributes appear to be highly correlated as evidenced by the close proximity of their direction vectors within the group space. A case could be made for calling dimension I a "generalized" return axis because of the several return vectors which follow its general direction, but such a conclusion would be tentative at best. Furthermore, dimension II appears devoid of potential candidate vectors which might provide clues as to the nature of the variable it represents. In summary, the list of variables by which respondents subjectively rated the eleven chemical stocks appears not to contain at least one, and possibly, two of the salient attributes or dimensions by which non-chemical analysts judged similarities and differences among these same stocks.

Figures 41, 42, and 43 illustrate the axis labeling results for the objectively calculated property vectors. Once again, not all the variables were located with sufficiently high r values to be shown and considered as potential axis labels. The numbers at the end of each direction vector in these figures refer to the listing of the statistical variables shown in Table 13.
FIGURE 41

OBJECTIVE PROPERTY VECTORS, NON-CHEMICAL ANALYSTS
GROUP CONFIGURATION SPACE (DIMENSION I VS. II)

[Diagram showing two dimensions with vectors labeled 1 through 21]
FIGURE 42

OBJECTIVE PROPERTY VECTORS, NON-CHEMICAL ANALYSTS
GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 43

OBJECTIVE PROPERTY VECTORS, NON-CHEMICAL ANALYSTS
GROUP CONFIGURATION SPACE (DIMENSION I VS. III)
The objective axis labels provide substantial additional information concerning the nature of non-chemical analysts' perceptual patterns. First, although no single property vector label can be assigned to dimension I, several of the direction vectors representing various "return" indicators appear to be aligned generally in the direction of axis I. These include "five-year E.P.S. growth," "five-year return on equity," and "five-year stock rise" (all from Forbes magazine)\(^7\) as well as "five-year geometric mean return" (from historical stock price data). These calculated return measures are highly correlated, and any one would apparently provide a satisfactory statistical label to dimension I of the non-chemical analyst configuration space.

Considerable evidence is also present to assign a "generalized risk" label to dimension II. As is shown, several of the historical risk variables, including "five-year modified quadratic mean," "five-year standard deviation," "five-year mean absolute deviation," and others are nearly colinear with dimension II. Since the average correlation coefficient among these calculated risk measures is quite high (.88) they could all be considered roughly equivalent in their usefulness as statistical labels for dimension II.

Finally, none of the objectively measured property vectors appears to be a suitable candidate for the labeling of dimension III. Thus the "expected dividend yield" label assigned from the examination of the subjective property vectors must still be considered valid.

In summary, certain similarities are discerned between the axis labeling results for the non-chemical analyst group and the chemical analyst respondents. In both groups, dimension III stood out clearly

\(^7\) Ibid.
from subjective evaluation data as an "expected dividend yield" axis. For the non-chemical analyst group, however, no satisfactory statistical surrogates were found for the subjective dividend yield estimates.

In the evaluation of dimension II, strong evidence exists that both analyst groups utilize this axis to differentiate between securities on the basis of perceived risk. Unfortunately, for neither group was a specific statistical risk label assigned because of a high degree of collinearity among appropriate property vectors and because of the apparent necessity for a slight rotation of dimension II before a close directional agreement with the various risk property vectors is achieved.

Only dimension I exhibits a substantial difference in nature between the two analyst groups. For the non-chemical group, this axis appears to be identified with a variety of what have been termed "generalized return" measures, implying a distinction among members of this group between the amount of total return from a security (dimension I) and the amount of dividend yield (dimension III) from similar investments. For the chemical analysts, however, dimension I was labeled "degree of liquidity" from the subjective evaluations, with the "five-year mean absolute deviation of returns" identified as a suitable statistical axis label.

C. Portfolio Managers—Chemical

Figures 44, 45, and 46 illustrate the PM-chemical group space derived from the application of the Carroll-Chang INDSCAL program to the 1 x 55 vectors of similarity judgments from fifteen portfolio managers who completed the "chemical" initial questionnaire. The three-dimensional group space was selected based on the average subject correlation coefficient results shown in Table 15. As is shown,
FIGURE 44

INDSCAL PORTFOLIO MANAGER-CHEMICAL GROUP
CONFIGURATION SPACE (DIMENSION I VS. II)

Dim II

Monsanto

DuPont

Dow

Celanese

Allied Chem.

Union Carb.

Dim I

PPG

Diam.

Shan.

Koppers

Commercial
Solvent

3M
FIGURE 45

INDSCAL PORTFOLIO MANAGER-CHEMICAL GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 46

INDSCAL PORTFOLIO MANAGER-CHEMICAL GROUP
CONFIGURATION SPACE (DIMENSION I VS. III)
TABLE 15
PORTFOLIO MANAGER-CHEMICAL INDSCAL AVERAGE
SUBJECT CORRELATION COEFFICIENTS

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.56</td>
</tr>
<tr>
<td>2</td>
<td>.66</td>
</tr>
<tr>
<td>3</td>
<td>.72</td>
</tr>
<tr>
<td>4</td>
<td>.73</td>
</tr>
<tr>
<td>5</td>
<td>.74</td>
</tr>
</tbody>
</table>

Beyond three dimensions little improvement in fit between the INDSCAL results and individual perceptual viewpoints is obtained. Within the PM-chemical group space it is seen that Commercial Solvents and, especially, 3M appear at extreme points along one or more axes, which is consistent with patterns observed in the examination of both the chemical analyst and non-chemical analyst group spaces.

Figures 47, 48, and 49 illustrate the results of the PROFIT axis labeling program using property vectors derived from the PM-chemical respondents' subjective ratings of the stimulus set on several potentially important investment attributes. As in previous discussions, the property vector identification numbers correspond to the variables listed in Table 12.

Examination of the axis labeling results shows that nine of the ten subjectively estimated property vectors could be located in the space so as to achieve significant correlations between subjective ratings and stimulus projections onto the property vectors. Dimension 1 appears to have few, if any, candidates for potential axis labels among the subjective variables. On the other hand, property vector 8 "expected short-term investment risk," appears to provide a suitable label for dimension 11.
SUBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-CHEMICAL
GROUP CONFIGURATION SPACE (DIMENSION I VS. II)
FIGURE 48

SUBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS - CHEMICAL
GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 49
SUBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-CHEMICAL
GROUP CONFIGURATION SPACE (DIMENSION I VS. III)
Figures 47 and 48 show that this vector is virtually colinear with dimension II when matched with either one of the other two axes. The r value for property vector 8 is .73, which is roughly average for the subjective property vectors. Although several other subjectively estimated vectors tend to be aligned with dimension II, none can seriously compete with the "short-term expected risk" vector in terms of colinearity and correlation with the ordering of securities along dimension II.

Finally, property vector 7, "expected short-term total return," appears to provide a suitable label for dimension III. This vector exhibits a close alignment with dimension III when paired with either of the other two axes, and has a computed r value of .71.

In terms of the subjectively estimated property vectors, therefore, both a risk axis (dimension II, short-term expected risk) and a return axis (dimension III, short-term total return) have been tentatively identified. No suitable label for dimension I was found.

Figures 50, 51, and 52 illustrate the axis labeling results for the statistically determined property vectors. Once again, no conclusive label for dimension I is apparent, although property vector 7, "one year geometric mean return," tends to align itself with dimension I. The calculated r value for this vector, however, is .66, which is only slightly above the level considered statistically significant. It appears that further research could very likely provide a far more conclusive identification of dimension I.

As for the other axes, several of the calculated risk variables are seen to lie in close proximity to dimension II. This result reinforces the tentative conclusion from the earlier, subjective results that this axis is identified with the portfolio managers' perceptions of investment risk. Of interest, however, is the fact that, while the
FIGURE 50

OBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-CHEMICAL GROUP CONFIGURATION SPACE (DIMENSION I VS. II)
FIGURE 51

OBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS—CHEMICAL GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 52

OBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-CHEMICAL
GROUP CONFIGURATION SPACE (DIMENSION I VS. III)
subjective labeling associated dimension II with short-term risk estimates, none of the short-term statistical risk variables achieved sufficiently high r values to be considered potential axis labels. As in previous results, however, the objectively calculated risk variables are so highly correlated that little distinction can be made between the resulting property vectors for these measures in order to apply a single statistical label to the risk axis. Thus dimension II must be termed a "generalized risk" axis until a sufficient differentiation between these statistical risk vectors is achieved.

A similar situation occurs in relation to dimension III. Several of the calculated return property vectors can be seen to lie generally along this axis, with no single measure providing an unambiguous label. If a "best" return vector had to be chosen to label dimension III, it would probably be vector 4, "five-year average annual earnings per share growth," which exhibits only minor tendencies along either of the other two axes.

In summary, although both a "risk" axis and a "return" axis have been clearly identified for the portfolio manager-chemical group space, precise statistical labels for these dimensions are not totally evident, primarily because (in the case of both dimensions II and III) several potential axis labels are highly correlated, causing the resulting property vectors to appear nearly equally valid as dimension identifiers. Little information concerning the nature of dimension I was obtained for the subjective property vectors, and the objective label applied to this axis (one year geometric mean return) is not considered conclusive.
D: Portfolio Manager-Diverse

The 1 x 55 vectors of similarity judgments obtained from fifteen portfolio managers on a diverse list of well-known common stocks were submitted to the Carroll-Chang INDSCAL program in order to obtain the group configuration space for these individuals. Table 16 shows the calculated "average subject correlation coefficient" for group spaces of varying dimensionalities. As is shown, beyond the two dimensional group space, only small increases in accuracy are observed. However, in order to be consistent with previous axis labeling discussions for the other investor groups, and because the "average" PM-diverse individual required three dimensions to achieve an "excellent" fit in terms of the Kruskal stress measure, the three-dimensional PM-diverse group configuration space was chosen for further analysis.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.65</td>
</tr>
<tr>
<td>2</td>
<td>.77</td>
</tr>
<tr>
<td>3</td>
<td>.81</td>
</tr>
<tr>
<td>4</td>
<td>.84</td>
</tr>
<tr>
<td>5</td>
<td>.86</td>
</tr>
</tbody>
</table>

Figures 53, 54, and 55 illustrate the three dimensional PM-diverse INDSCAL group space result. As with the group spaces constructed from the chemical list of stocks, examination of the companies lying at the

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8 See Figure 15, Chapter IV.
FIGURE 53
INDSCAL PORTFOLIO MANAGERS - DIVERSE GROUP
CONFIGURATION SPACE (DIMENSION I VS. II)

Dim II

INA

Jersey

AZ&T

Dim I

IBM

Sears

Avon

Polaroid

Burroughs

Warn.-Lamb.
FIGURE 54
INDSCAL PORTFOLIO MANAGERS-DIVERSE GROUP
CONFIGURATION SPACE (DIMENSION II VS. III)

Dim III

Sears

AT&T

Jersey

3M

Warn.-Lamb.

IBM

INA

Dim II

Polaroid

Burroughs

Amer. Air
FIGURE 55
INDSCAL PORTFOLIO MANAGERS-DIVERSE GROUP
CONFIGURATION SPACE (DIMENSION I VS. III)
extremes of the dimensions of the PM-diverse space offers little evidence in terms of axis identification. In general, American Airlines, INA, A.T.&T., and Sears-Roebuck appear to be located at relatively extreme positions along the various axes.

Figures 56, 57, and 58 illustrate the results of the PROFIT axis labeling program to the PM-diverse group configuration space and property vectors derived from the individuals' subjective ratings of the stocks on the investment attributes listed in the follow-up questionnaire. As is shown, eight of the ten subjective property vectors achieved significant correlation coefficients when located in the PM-diverse group space. From this data, certain initial inferences concerning salient perceptual variables can be made. Dimension I appears to represent a "long-term expected return" axis in the PM-diverse perceptual pattern. Both property vectors 1, "long-term earnings per share growth," and vector 2, "long-term total return," are seen to be nearly colinear with dimension I in Figures 56 and 58, and to lie between dimensions II and III in Figure 57. The calculated r values for vectors 1 and 2 are .95 and .91 respectively, both highly significant.

Dimension II appears to have no satisfactory label among the subjectively estimated attributes by which the portfolio managers rated each stock on the diverse list. None of the property vectors have dimension II components which are sufficiently large to cause serious consideration of them as possible axis labels.

Two subjective vectors, "liquidity" and "quality of management" are identified as potential labels for dimension III. Property vector 5, "liquidity" is selected as the better of the two labels because of its higher degree of colinearity with axis III (shown in Figures 57 and 58).
FIGURE 56

SUBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-DIVERSE
GROUP CONFIGURATION SPACE (DIMENSION I VS. II)
SUBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-DIVERSE GROUP CONFIGURATION SPACE (DIMENSION II VS. III)
FIGURE 58
SUBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-DIVERSE
GROUP CONFIGURATION SPACE (DIMENSION I VS. III)
and because of its higher correlation coefficient (.82 for liquidity vs. .79 for quality of management).

To this point, then, tentative labels have been assigned to two of the three dimensions of the PM-diverse group space. Dimension I appears to be highly correlated with portfolio manager's subjective rankings of the diverse list of stocks on the basis of long-term investment returns, while dimension III appears to be aligned with respondents' evaluations of the relative liquidity of the investment alternatives.

Only dimension II remains totally undefined to this point. However, it should be noted that, although the subjectively estimated risk vectors ("long-term investment risk" and "short-term investment risk") did not achieve statistically significant correlation values to be shown in Figures 56-58, both were located by the PROFIT program generally along dimension II of the group configuration space. This is at least a preliminary indication of the nature of this axis within the PM-diverse perceptual pattern.

Significant additional evidence concerning salient variables in the investment evaluation processes of portfolio managers is obtained from the application of the PROFIT axis-labeling program to the objectively calculated property vectors. These results are illustrated in Figures 59, 60, and 61. In general, the tentative conclusions from the "subjective" property vector analysis discussed above are confirmed and amplified by the objective data.

First, dimension I is strongly confirmed as a "long-term return" axis. Both property vectors 8, "five-year arithmetic average monthly return," and vector 9, "five-year geometric mean monthly return" are seen to be located almost colinearly with dimension I. These vectors have correlation coefficients of .75 and .77, respectively. In addition,
FIGURE 59

OBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-DIVERSE
GROUP CONFIGURATION SPACE (DIMENSION I VS. II)

Includes Vectors
10,12,13,14,15,16,18,19,20,21
FIGURE 60

OBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-DIVERSE
GROUP CONFIGURATION SPACE (DIMENSION II VS. III)

Includes Vectors
10, 12, 14, 15, 16, 18, 19, 20, 21
FIGURE 61
OBJECTIVE PROPERTY VECTORS, PORTFOLIO MANAGERS-DIVERSE
GROUP CONFIGURATION SPACE (DIMENSION I VS. III)

Includes Vectors 10, 12, 14, 13, 15, 16, 18, 19, 20, 21
two of the Forbes return vectors, "five-year annual earnings per share growth" and "five-year stock rise" are also seen to have sizeable dimension I components. It is apparent that dimension I can be identified as a "return" axis within the perceptual pattern of the PM-diverse individual, with "five-year arithmetic average monthly return" appearing to provide the most precise statistical definition for this perceptual attribute.

As intimated from the earlier examination of the subjective property vectors, dimension II appears in these figures to represent a risk axis. As is shown, several of the statistical risk measures exhibit a high degree of colinearity with dimension II in Figures 59 and 60, while falling roughly between dimensions I and III in Figure 61. Unfortunately, because of the high degree of intercorrelation among these calculated risk measures, no meaningful distinctions can be drawn between them for precise axis labeling purposes. Furthermore, it appears that a slight rotation of dimension II would achieve an even better overall degree of colinearity between the axis and the risk property vectors. For these reasons, no precise statistical risk label will be applied at this time to dimension II of the PM-diverse group configuration space.

Finally, no strong candidates to provide a label for dimension III appear from the statistical variables. Vectors number 1, "five-year return on equity" and 2, "five-year return on total capital" are observed to have sizeable dimension III components. However, the degree of colinearity with axis 3, plus the calculated correlation coefficients (.80 and .82, respectively) are not sufficiently compelling to use these vectors as a basis for assigning a precise label to dimension III.

In summary, axis labeling efforts based on both the subjectively estimated and objectively calculated sets of property vectors
lead to the identification of both a risk axis and a return axis within the PM-diverse configuration space. Dimension III is tentatively labeled as "liquidity" from the subjective ratings of the PM-diverse individuals.

E. Summary

The objective of the evaluation of Hypothesis 4 was to learn what factors or variables are most important in determining the way in which important investor groups perceive or distinguish between investment alternatives. Through the use of the PROFIT axis labeling program and a variety of both subjectively estimated and objectively calculated property vectors, considerable insight has been gained into the perceptual patterns of the respondents surveyed in this research.

First, within the configuration spaces of each of the four investor groups surveyed it was possible to tentatively identify both a risk and a return dimension. In general, conclusions along these lines derived from the subjective property vectors were confirmed by the objective vectors, at times allowing precise statistical labels to be applied to various axes of the configuration spaces. However, it must be noted that, in several instances, specific statistical labels could not be assigned to a dimension, even though its general nature (i.e., return, risk) had been identified. This situation arose either because (a) several property vectors were highly correlated and thus so closely aligned that distinguishing between them was inappropriate, or (b) it appeared that a slight rotation of the axis would be required to bring it into close alignment with one or more of the list of property vectors used in this research.

In terms of the property vectors themselves, it is interesting to note that a far higher percentage of the "long-term" (objective or estimated) property vectors achieved significant correlation coefficients
than did the "short-term" variables. In almost no cases did the short-
term property vectors obtained from stock price movements over the pre-
vious twelve months achieve significant correlation coefficients, and
in only the PM-chemical group space did short-term subjectively esti-
mented property vectors (both risk and return) provide acceptable axis
labels.

Finally, it is interesting to note the appearance of "expected
dividend yield" as a dimension label in the configuration spaces of
both security analyst groups. This variable appears as the only identi-
fiable return dimension in the chemical analyst group space, and in
addition to a "generalized return" axis in the non-chemical analyst
space. Neither of the portfolio manager groups appeared to consider
dividend yield as a salient investment attribute, perhaps implying an
identifiable distinction in viewpoint or evaluative criteria between
individuals who provide investment recommendations (security analysts)
and those individuals who must act on the recommendations (portfolio
managers).

H5: An inverse relationship exists between stimulus-ideal point
distances in an individual or group "joint space" and the de-
gree of preference for a given security exhibited by individuals
or groups in the construction of hypothetical portfolios.

Hypothesis 4 was concerned with the attempt to formulate
descriptive models of the way in which important investor groups per-
ceive similarities and differences among common stocks. The objective
of H5 is to determine whether the information about individual and
group perceptual patterns gathered to this point can be combined with
preference data from these same respondents to construct predictive models
of investment behavior whose adequacy can be evaluated and, hopefully, con-
firmed by comparing predicted results with subsequent investor behavior.
As noted in Chapter III, the Carroll-Chang PREF-MAP program will be used to construct the "joint space" of both stimulus points and ideal points generated from the combining of either individual or group space stimulus coordinates with preference rankings for the common stocks in the stimulus set. As described in Chapter III, F-type statistics are used to determine the precise form of the utility function (or "phase") which best represents the preference data inputted to the program.

Three different approaches will be used within each investor group to construct joint spaces and to obtain the resultant predictions of investor behavior. First, separate joint spaces for each individual will be formed by combining his own unique configuration space derived from the MDSCAL applications discussed in Hypothesis 1 with his own ranking of the eleven stimulus securities by preference obtained in the initial questionnaire. This procedure will, in effect, provide a unique predictive model for each individual. A second approach to joint space construction will use the coordinates of the group configuration spaces (in three dimensions) used in the evaluation of $H_q$, in combination with the averaged preference ratings of all members of the given group. This will provide a single "group ideal point" within the group configuration space. Finally, the individual preference ratings of each member of a given group will be combined with the coordinates of the group configuration space. This will result in distinct individual ideal points within the over-all group configuration space.

The procedures described above will be performed for each of the four respondent groups. The predictive models so constructed will then be evaluated by comparing predicted investment behavior (based on the proximity of various stimulus points to either individual or group ideal points) with the decisions actually made by respondents in the construction
of hypothetical investment portfolios from the stimulus securities. In this manner an initial assessment of the feasibility of using multi-dimensional scaling techniques in the development of predictive models of investment behavior can be made.

A: Chemical Analysts

1. Individual Spaces

The three-dimensional coordinates from each chemical analyst's original MDSCAL scaling solution were combined with his own idiosyncratic preference rankings for the eleven common stocks and submitted to the Carroll-Chang PREF-MAP program in order to construct a unique "joint space" for each individual. Table 17 summarizes the results of this analysis. Each row of the table corresponds to one of the chemical analyst (CA) respondents. Of the original thirteen chemical analysts whose initial questionnaires were judged acceptable for earlier scaling analyses, only eleven provided acceptable preference data for use in the construction of an individual joint space. The first eleven columns of this table are identifiable as the eleven stimulus securities, while the subsequent columns note the PREF-MAP "phase" considered appropriate for that individual's preference function, and the sign of the axis weights in the final stimulus-ideal point distance calculation. Within the body of the table, the numbers refer to the "distance" between the ideal point and the various stimulus of "stock" points. A bar above one of these numbers means that the stock corresponding to the column in which the number is found was one of those selected by that individual in his hypothetical optimal portfolio.

Two clarifications must be made immediately. The first is that many of the "distances" shown in Table 17 (and later tables of this type)
<table>
<thead>
<tr>
<th>Individual</th>
<th>Security</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th>Phase</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>I</td>
<td>II</td>
<td>III</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>1.02</td>
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<td>.91</td>
<td>.71</td>
<td>1.10</td>
<td>.45</td>
<td>III</td>
</tr>
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<td>-.55</td>
<td>-.54</td>
<td>-.62</td>
<td>-.58</td>
<td>-.61</td>
<td>-.60</td>
<td>-.57</td>
<td>-.53</td>
<td>-.53</td>
<td>-.53</td>
<td>III</td>
</tr>
<tr>
<td>CA-3</td>
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<td>1.08</td>
<td>-.41</td>
<td>-.90</td>
<td>-2.18</td>
<td>-5.82</td>
<td>-2.83</td>
<td>-4.25</td>
<td>2.16</td>
<td>-2.28</td>
<td>III</td>
</tr>
<tr>
<td>CA-4</td>
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<td>-1.90</td>
<td>-1.69</td>
<td>-2.27</td>
<td>-2.51</td>
<td>-2.36</td>
<td>-2.53</td>
<td>-1.79</td>
<td>-2.14</td>
<td>-1.53</td>
<td>-2.08</td>
<td>III</td>
</tr>
<tr>
<td>CA-5</td>
<td>.07</td>
<td>4.06</td>
<td>3.09</td>
<td>-1.93</td>
<td>-3.94</td>
<td>-.90</td>
<td>-2.88</td>
<td>2.07</td>
<td>1.03</td>
<td>5.09</td>
<td>4.97</td>
<td>III</td>
</tr>
<tr>
<td>CA-6</td>
<td>-1.51</td>
<td>-1.66</td>
<td>-2.94</td>
<td>-6.19</td>
<td>-6.55</td>
<td>-1.93</td>
<td>-6.76</td>
<td>-4.19</td>
<td>-.40</td>
<td>1.65</td>
<td>-.83</td>
<td>III</td>
</tr>
<tr>
<td>CA-7</td>
<td>-5.64</td>
<td>-7.84</td>
<td>-4.22</td>
<td>-8.61</td>
<td>-10.92</td>
<td>-9.21</td>
<td>-9.80</td>
<td>-12.53</td>
<td>-8.76</td>
<td>-2.68</td>
<td>-3.51</td>
<td>III</td>
</tr>
<tr>
<td>CA-8</td>
<td>-3.43</td>
<td>1.16</td>
<td>4.19</td>
<td>-2.29</td>
<td>-1.83</td>
<td>-2.59</td>
<td>-3.74</td>
<td>-5.12</td>
<td>-5.01</td>
<td>2.50</td>
<td>.24</td>
<td>III</td>
</tr>
<tr>
<td>CA-10</td>
<td>16.75</td>
<td>17.41</td>
<td>18.94</td>
<td>11.66</td>
<td>10.89</td>
<td>15.61</td>
<td>12.57</td>
<td>13.71</td>
<td>14.92</td>
<td>19.44</td>
<td>17.71</td>
<td>III</td>
</tr>
<tr>
<td>CA-11</td>
<td>-4.21</td>
<td>-1.87</td>
<td>-3.46</td>
<td>-5.62</td>
<td>-8.94</td>
<td>-6.94</td>
<td>-6.31</td>
<td>-3.66</td>
<td>-.14</td>
<td>1.41</td>
<td>-.11</td>
<td>III</td>
</tr>
</tbody>
</table>
are negative. This fact arises from a combination of the presence of negative axis weightings and the manner in which the program calculates its stimulus-ideal point distance measure. For instance, at times during the evaluation of the interrelationship between the stimulus configuration and preference rankings, the PREF-MAP program will conclude that one or more of the configuration dimensions should be negatively weighted in terms of preference. That is, the closer a security is to the "ideal point" along that dimension, the less it is preferred, and vice versa. This result is indicated in the PREF-MAP routine by showing a negative weight for that dimension. When precise stimulus-ideal point distances are calculated, the program retains the negative weighting throughout the distance calculation, at times resulting in a net overall negative "distance" between the two points. In the evaluation of this distance measure the rule which must be used is that "the lower the distance measure, the better." Thus, a security whose "distance" from the ideal point is measured as -1.00 will be presumed to represent a more highly preferred investment than one whose stimulus-ideal point distance is +1.00.

Second, in virtually every PREF-MAP application performed during this research, the form of the utility function which was found to be most appropriate for use with either individual or group preference data was the Carroll-Chang Phase 3 utility model, which constrains configuration axes to identical stretching or compression, save only for variations in the sign of the weightings. No differential stretching, nor any axis rotations are permitted in the Phase 3 utility assumptions. Table 18 shows the statistical comparison data for the various PREF-MAP phases derived from the stimulus coordinates and preference rankings of individual CA-5. These results are typical of the PREF-MAP results
experienced during calculation of both individual and group joint spaces. The correlation data shows that model 4 is definitely inferior to the others in describing investor preference patterns, yet analysis of the F statistics between the various models shows that the more complex utility models (1 and 2) add almost nothing to the fit achieved with Phase III.

**TABLE 18**

**COMPARISON OF FOUR PREF-MAP UTILITY MODELS FOR SUBJECT CA-5**

Correlations and F-Ratios for Four Models

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlations</td>
<td>.96</td>
<td>.96</td>
<td>.96</td>
<td>.77</td>
</tr>
<tr>
<td>F-Ratios</td>
<td>1.30</td>
<td>7.79*</td>
<td>17.52**</td>
<td>3.45</td>
</tr>
<tr>
<td>(9,1) d.f.</td>
<td>(6,4) d.f.</td>
<td>(4,6) d.f.</td>
<td>(3,7) d.f.</td>
<td></td>
</tr>
</tbody>
</table>

F-Ratios Between Four Models

<table>
<thead>
<tr>
<th></th>
<th>F 12</th>
<th>F 13</th>
<th>F 14</th>
<th>F 23</th>
<th>F 24</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>.685</td>
<td>0.00</td>
<td>5.48</td>
</tr>
<tr>
<td>(3,1) d.f.</td>
<td>(5,1) d.f.</td>
<td>(6,1) d.f.</td>
<td>(2,4) d.f.</td>
<td>(3,4) d.f.</td>
<td></td>
</tr>
</tbody>
</table>

*Significant at .05 level. Critical value = 6.16
**Significant at .01 level. Critical value = 9.15

The conclusion for this and all other individuals was that the utility model described as Phase 3 in the Carroll-Chang PREF-MAP program was the most appropriate model upon which to base further analyses and subsequent investment predictions.

Turning once again to Table 17, individual CA-1 fails to exhibit the hypothesized pattern of investment behavior. His investment
selections bear no discernible relationship to the stimulus ideal point distances calculated from his unique "joint space." For the other chemical analysts, however, it is apparent that the hypothesized relationship between stimulus-ideal point distances and investment behavior holds very well. In virtually every case, the securities with the lowest calculated distance measures between the security coordinate and the ideal point are the ones selected by the analysts for inclusion in their optimal portfolio. This situation holds true for analysts CA-2, 3, 5, 6, 8, 10, and 11. Only minor deviations from this pattern are exhibited by the other chemical analysts. It is also interesting to note that the order in which securities were selected for hypothetical portfolios, although not shown on Table 17, was, in many cases, precisely the order that would be predicted from the calculated stimulus-ideal point distance data. In other words, the first stock selected by an individual generally had the lowest computed stimulus-ideal point distance, the second selection the next lowest, and so on. This is further confirmation of the hypothesis that individual investment behavior (of the type observed in the construction of hypothetical portfolios) can be modeled and predicted by multidimensional scaling techniques.

Table 19 shows the average stimulus-ideal point distances of securities chosen by chemical analysts for their hypothetical optimal portfolios compared to the distances for the stocks which were not selected. The results are precisely what was hypothesized and expected based on results to this point; the average stimulus-ideal point distances for selected stocks are consistently (and, in most cases, significantly) less than those of the stocks not chosen by the analysts.
TABLE 19
CHEMICAL ANALYSTS' AVERAGE PREF-MAP STIMULUS-IDEAL POINT
DISTANCES FOR SELECTED VS. NON-SELECTED STOCKS
(INDIVIDUAL JOINT SPACES)

<table>
<thead>
<tr>
<th>Individual</th>
<th>Mean Distance: Selected Stocks</th>
<th>Mean Distance: Non-Selected Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA- 1</td>
<td>.94</td>
<td>.67</td>
</tr>
<tr>
<td>CA- 2</td>
<td>-.60</td>
<td>-.54</td>
</tr>
<tr>
<td>CA- 3</td>
<td>5.34</td>
<td>.67*</td>
</tr>
<tr>
<td>CA- 4</td>
<td>2.28</td>
<td>1.95</td>
</tr>
<tr>
<td>CA- 5</td>
<td>2.92</td>
<td>2.32*</td>
</tr>
<tr>
<td>CA- 6</td>
<td>5.92</td>
<td>1.09*</td>
</tr>
<tr>
<td>CA- 7</td>
<td>-10.50</td>
<td>5.96*</td>
</tr>
<tr>
<td>CA- 8</td>
<td>4.98</td>
<td>.66*</td>
</tr>
<tr>
<td>CA- 9</td>
<td>8.65</td>
<td>4.38*</td>
</tr>
<tr>
<td>CA-10</td>
<td>10.89</td>
<td>15.87*</td>
</tr>
<tr>
<td>CA-11</td>
<td>6.34</td>
<td>1.31*</td>
</tr>
</tbody>
</table>

*Difference in means are statistically significant at $\alpha = .05$ level.

2. Group Spaces

Computing individual configuration spaces for every individual is
an inefficient and laborious process. An alternative is to utilize a
single group configuration space for all members of a homogeneous group,
then to locate within this space either individual ideal points or, if
accuracy allows, a single "average" ideal point which summarizes the
preference data for all members of the group. Both approaches will be
evaluated in this section.

First, individual preference data from all chemical analysts were
combined with the three-dimensional chemical analyst group space co-
dinates obtained from Chapter IV to form a "joint" space of stimulus
points and multiple ideal points, one for each chemical analyst. As before, utility model III from the PREF-MAP program was found to provide the best over-all summarization and display of the preference judgments. This utility model allows each individual to utilize his own unique set of axis weights, with the constraint that the dimension weights must all be equal except for sign changes. No rotation of the group space axes is permitted.

Table 20 summarizes the results of this PREF-MAP application. As before, individual stimulus-ideal point distances (calculated from each individuals' unique ideal point to the stimulus coordinates) are shown, with the bar overhead identifying those stocks selected by the analyst for his hypothetical portfolio. (Disregard, for a moment, the "average" individual). As is seen, results are generally the same as in Table 17, although some slight loss in accuracy may be noted. Individual CA-1 certainly now conforms much more to the hypothesized preference pattern, but for others some slight incongruities between stimulus-ideal point distances and portfolio selection behavior have appeared which were not seen in the individual PREF-MAP calculations. CA-6, for example, shows a slightly lower distance value for Monsanto than for Celanese, although he chose Celanese for his portfolio. These are only minor discrepancies, however, and cannot obscure the overall pattern or relationship between computed distance and likelihood of selection by an analyst for his optimal portfolio. Table 21, which shows the average stimulus-ideal point distances for those stocks selected versus the stocks not chosen, further confirms the validity of the preference model constructed to this point. Thus, after one "stage" of summarization (the construction of a single group configuration space) the predictive ability of the
<table>
<thead>
<tr>
<th>Individual</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>Phase</th>
<th>Axis Weight</th>
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</thead>
<tbody>
<tr>
<td>CA-1</td>
<td>1.84</td>
<td>.69</td>
<td>1.56</td>
<td>-5.40</td>
<td>.01</td>
<td>-2.43</td>
<td>-2.36</td>
<td>-2.41</td>
<td>1.36</td>
<td>3.36</td>
<td>2.98</td>
<td>III</td>
<td>-</td>
</tr>
<tr>
<td>CA-3</td>
<td>-38.28</td>
<td>-36.16</td>
<td>-35.50</td>
<td>-41.19</td>
<td>-42.69</td>
<td>-38.48</td>
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<td>-39.23</td>
<td>-35.26</td>
<td>-36.09</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
<td>CA-4</td>
<td>6.19</td>
<td>6.44</td>
<td>6.51</td>
<td>5.91</td>
<td>5.71</td>
<td>6.19</td>
<td>5.82</td>
<td>6.20</td>
<td>6.09</td>
<td>6.53</td>
<td>6.43</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
<td>CA-5</td>
<td>1.72</td>
<td>1.95</td>
<td>2.04</td>
<td>1.39</td>
<td>1.20</td>
<td>1.65</td>
<td>1.31</td>
<td>1.66</td>
<td>1.66</td>
<td>2.07</td>
<td>1.97</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
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<td>2.17</td>
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<td>2.15</td>
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<td>+</td>
</tr>
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<td>.35</td>
<td>2.12</td>
<td>8.23</td>
<td>6.38</td>
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<td>+</td>
</tr>
<tr>
<td>CA-8</td>
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<td>11.53</td>
<td>7.51</td>
<td>5.71</td>
<td>5.35</td>
<td>6.59</td>
<td>4.96</td>
<td>3.33</td>
<td>12.95</td>
<td>10.80</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
<td>CA-9</td>
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<td>1.39</td>
<td>2.27</td>
<td>6.92</td>
<td>7.11</td>
<td>1.41</td>
<td>6.88</td>
<td>.96</td>
<td>.44</td>
<td>3.00</td>
<td>2.37</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
<td>CA-11</td>
<td>5.38</td>
<td>6.53</td>
<td>7.33</td>
<td>1.03</td>
<td>.84</td>
<td>2.80</td>
<td>.64</td>
<td>2.77</td>
<td>7.12</td>
<td>7.38</td>
<td>6.55</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
<td>Average</td>
<td>6.93</td>
<td>8.42</td>
<td>9.47</td>
<td>4.36</td>
<td>3.91</td>
<td>5.41</td>
<td>4.34</td>
<td>5.34</td>
<td>6.47</td>
<td>10.17</td>
<td>9.16</td>
<td>III</td>
<td>+</td>
</tr>
</tbody>
</table>
multidimensional preference model continues to be quite high. The next step in summarization is to combine the individual ideal points into a single chemical analyst average group ideal point within the group configuration space, and to evaluate the degree of predictive ability retained by such a calculation.

**TABLE 21**

**CHEMICAL ANALYSTS' AVERAGE PREF-MAP STIMULUS-IDEAL POINT DISTANCES FOR SELECTED VS. NON-SELECTED STOCKS ("GROUP" CONFIGURATION SPACE)**

<table>
<thead>
<tr>
<th>Individual</th>
<th>Mean Distance: Selected Stocks</th>
<th>Mean Distance: Non-Selected Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA-1</td>
<td>-3.15</td>
<td>1.69*</td>
</tr>
<tr>
<td>CA-2</td>
<td>-12.13</td>
<td>-6.48*</td>
</tr>
<tr>
<td>CA-3</td>
<td>-41.30</td>
<td>-36.90</td>
</tr>
<tr>
<td>CA-4</td>
<td>6.03</td>
<td>6.31</td>
</tr>
<tr>
<td>CA-5</td>
<td>1.30</td>
<td>1.84</td>
</tr>
<tr>
<td>CA-6</td>
<td>1.66</td>
<td>2.14</td>
</tr>
<tr>
<td>CA-7</td>
<td>1.15</td>
<td>4.67*</td>
</tr>
<tr>
<td>CA-8</td>
<td>5.21</td>
<td>9.67*</td>
</tr>
<tr>
<td>CA-9</td>
<td>1.05</td>
<td>4.26*</td>
</tr>
<tr>
<td>CA-10</td>
<td>9.53</td>
<td>9.99</td>
</tr>
<tr>
<td>CA-11</td>
<td>1.80</td>
<td>6.28*</td>
</tr>
</tbody>
</table>

*Difference in means are statistically significant at \( \alpha = .05 \) level.

Table 20 shows the results of this averaging. Preference data was averaged across all members of the chemical analyst group and submitted to the PEF-MAP program. This procedure located an "average" analyst ideal point within the chemical analyst group space and resulted in the stimulus-ideal point distances contained in the "Average" row of Table 20.
Table 22 shows the degree to which the rankings of stocks on the basis of their proximity to the group ideal point conforms to the investment behavior of the entire group in their construction of hypothetical portfolios. Using the Spearman Rank Correlation Coefficient (corrected for ties)\(^9\) as the measure of association between predicted results (column 1) and investment "behavior" (columns 2 and 3) provides conclusive evidence as to the continued success, even at this stage of summarization, of the MDS approach to constructing predictive investment models. Thus, the Spearman rank correlation coefficient between distance (column 1) and number of times selected (column 2) is .92, while the correlation between distance (column 1) and the total dollar amount invested by group members (column 3) drops off slightly to .83. Both results are statistically significant.\(^10\)

In summary, the PREF-MAP results at all levels of summarization are highly encouraging. At the individual analyst level, the predicted correspondence between stimulus-ideal point distances and subsequent investment behavior is clearly apparent. Although a slight loss of accuracy can be discerned, the placing of individual ideal points in a single group space still provides a high degree of predictive accuracy. Finally, even locating a single "average" ideal point in the group configuration space results in predictions about over-all "group" preference which are highly correlated with measures of subsequent group investment behavior.

---


\(^10\)Ibid. p. 206.
TABLE 22
CHEMICAL ANALYSTS' PREFERENCE RANKINGS
OF STIMULUS COMMON STOCKS

<table>
<thead>
<tr>
<th></th>
<th>(1) Distance Within Group Joint Space (1 = lowest)</th>
<th>(2) Times Chosen For Hypothetical Portfolios (1 = most)</th>
<th>(3) Dollars Allocated in Hypothetical Portfolios (1 = most)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PPG</td>
<td>7</td>
<td>7</td>
<td>8 (tie)</td>
</tr>
<tr>
<td>2. Allied</td>
<td>8</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>3. Diam. Sham.</td>
<td>10</td>
<td>9 (tie)</td>
<td>8 (tie)</td>
</tr>
<tr>
<td>4. DuPont</td>
<td>3</td>
<td>3 (tie)</td>
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<td>6. Mon.</td>
<td>5</td>
<td>3 (tie)</td>
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<td>1</td>
</tr>
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<td>8. Celanese</td>
<td>4</td>
<td>3 (tie)</td>
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<td>9. Union Carb.</td>
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<td>3 (tie)</td>
<td>3</td>
</tr>
<tr>
<td>10. Commer. Solv.</td>
<td>11</td>
<td>9 (tie)</td>
<td>8 (tie)</td>
</tr>
<tr>
<td>11. Koppers</td>
<td>9</td>
<td>9 (tie)</td>
<td>11</td>
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</table>

Before turning to the other investor groups in this research, brief mention should be made of the relation between the signs of the axis weightings for the chemical analysts and the earlier axis labeling results. Above, when individual ideal points were located in the chemical analyst group configuration space, this action consistently resulted in a negative weighting being assigned to dimension III of the group space (see Table 20). Such a weighting was presumably required in order to provide the best "fit" between individual preference rankings and the stimulus-ideal point distances resulting from the PREF-MAP calculation. Since dimension III was labeled "expected dividend yield" during the evaluation of hypothesis 4, the conclusion must be drawn that, in general, the
chemical security analysts considered dividend yield as a negative factor, both in their evaluations and in their own investment selections. It is possible that this dividend avoidance is a result of the investment attitudes and objectives of the "clients" for whom the chemical analysts provide recommendations (i.e., growth-type mutual funds, personal investment advisers, pension funds, etc.). However, the precise explanation for this phenomenon must be considered unresolved at this time. None of the other dimensions had consistently negative weightings.

B: Non-Chemical Analysts

1. Individual Spaces

As before, the three-dimensional coordinates from each non-chemical analyst's original MDSCAL results were combined with his unique preference rankings to form an individual "joint space." Table 23 summarizes the results of this analysis. As before, bars over the stimulus-ideal point distances indicate securities selected by the various individuals for their own hypothetical portfolios. It should be noted that one of the nineteen non-chemical analysts whose initial questionnaires were used in earlier analyses provided incomplete preference data, leaving eighteen respondents with acceptable responses for further PREF-MAP calculations.

The results shown in Table 23 are generally similar to those obtained from the chemical analyst respondents. In most cases, the hypothesized relationship between stimulus-ideal point distances and investment selection is quite clear. Only individuals NC-2, NC-3, NC-6, NC-8, NC-13, and NC-18 show even minor deviations from the predicted pattern. Table 24 shows the average stimulus-ideal point distances of securities chosen by non-chemical analysts for their hypothetical optimal portfolios in relation to the average distances for stocks not chosen.
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### Table 24

**Non-Chemical Analysts' Average Pref-Map Stimulus Ideal Point Distances for Selected vs. Non-Selected Stocks (Individual Joint Spaces)**

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<th>Mean Distance: Non-Selected Stocks</th>
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<tr>
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<tr>
<td>NC-14</td>
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<td>2.23</td>
<td>6.84*</td>
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</table>

* Differences in means are statistically significant at \( \alpha = .05 \) level.
As hypothesized, the average stimulus-ideal point distances for stocks not selected are consistently (and significantly) higher than those of the stocks chosen by the analysts. On an individual analyst basis, then, the PEF-MAP predictive model must be considered highly accurate. It should be noted that the "Phase III" utility function was selected as most appropriate for all non-chemical analyst subjects, consistent with earlier findings for the chemical analyst group.

2. Group Spaces

As before, the coordinates of the non-chemical analyst group configuration space from H4 were combined in the PEF-MAP program with individual preference data to form a single "joint space" containing unique individual ideal points.

Table 25 summarizes the results of this calculation, and shows that some loss of predictive accuracy has occurred. In general, some individuals whose results were in perfect conformance to predicted patterns with the individual joint spaces now exhibit minor deviations from the hypothesized investment behavior when placed in the group configuration space. On the other hand, for those analysts whose individual joint spaces were less than totally successful in predicting investment behavior, no serious additional loss of accuracy can be discerned in their "group space" results. Table 26 shows that, after one stage of summarization, average stimulus-ideal point distances for stocks selected by the non-chemical analysts are still significantly below the average for stocks not chosen.

The "average" individual shown on Table 25 results from the summarizing of the individual preference rankings from the eighteen non-chemical analysts and the resulting location, within the group
TABLE 25

STIMULUS-IDEAL POINT DISTANCES, NON-CHEMICAL ANALYSTS,
GROUP CONFIGURATION SPACE

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</table>

*Differences in means are statistically significant at α = .05 level.*
configuration space, of a single "average" non-chemical analyst ideal point. The stimulus-ideal point distances obtained from this calculation are rank ordered in Table 27, along with orderings of the stimulus securities in terms of the number of times chosen for a hypothetical portfolio (column 2) and the total amount of dollars "invested" by all the non-chemical analysts in each stock (column 3). The Spearman rank correlation coefficients between columns 1 and 2 and columns 1 and 3 are .88 and .92, respectively. Both values are statistically significant at $\alpha = .05$.

### TABLE 27

**NON-CHEMICAL ANALYSTS' PREFERENCE RANKINGS OF STIMULUS COMMON STOCKS**

<table>
<thead>
<tr>
<th>Stock</th>
<th>(1) Distance Within Group Joint Space</th>
<th>(2) Times Selected For Portfolio</th>
<th>(3) Dollars Invested In Stock</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PPG</td>
<td>7</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>2. Allied Chem.</td>
<td>8</td>
<td>9 (tie)</td>
<td>8</td>
</tr>
<tr>
<td>3. Diam. Sham.</td>
<td>9</td>
<td>9 (tie)</td>
<td>10 (tie)</td>
</tr>
<tr>
<td>4. DuPont</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>5. MMM</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>6. Monsanto</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>7. Dow</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>8. Celanese</td>
<td>6</td>
<td>6 (tie)</td>
<td>7</td>
</tr>
<tr>
<td>9. Union Carb.</td>
<td>5</td>
<td>6 (tie)</td>
<td>5</td>
</tr>
<tr>
<td>10. Commer. Solv.</td>
<td>10</td>
<td>6 (tie)</td>
<td>9</td>
</tr>
<tr>
<td>11. Koppers</td>
<td>11</td>
<td>11</td>
<td>10 (tie)</td>
</tr>
</tbody>
</table>
In summary, the PREF-MAP results for the non-chemical analyst group continue to provide a high degree of predictive accuracy. Results at the individual analyst level were quite good, although it appeared that a greater loss of accuracy occurred for the non-chemical analyst subjects in the move from individual spaces to the "group" configuration space than was observed for the chemical analysts. Even at the highest level of summarization, however, the single "average" ideal point was shown to provide highly accurate predictions about the subsequent investment "behavior" of the non-chemical analyst respondent group.

As a final point in this section, the application of a negative weight to dimension III of the non-chemical group space, identified as "long-term expected dividend yield" in $H_4$, was far less pronounced for these subjects than for the chemical analysts, indicating a much less negative attitude, at least in terms of chemical securities, toward dividend yield. This result was accompanied by a far higher percentage of individuals with negative weights applied to dimension II. Such a result would be expected based on the "generalized risk" label applied to this dimension in the evaluation of $H_4$. In addition, no individuals weighted axis I negatively, a comforting result considering the "generalized return" label previously applied to this dimension. Thus, the PREF-MAP axis weightings offer at least tentative confirmation of the conclusions drawn during earlier axis-labeling efforts.

C: Portfolio Managers--Chemical

1. Individual Spaces

As with the two analyst groups discussed previously, the three dimensional coordinates from each portfolio manager-chemical subject's individual MDSCAL results were combined with the individual preference
rankings to form a unique joint space for each PM-chem respondent. The resulting stimulus-ideal point distances from the idiosyncratic joint spaces are shown in Table 28. Once again, it is apparent that the actual investment behavior of these portfolio managers in the formation of optimal portfolios from the chemical list of securities follows the expected pattern. That is, the stocks with the greatest proximity to the subject's ideal point (as measured in PREF-MAP "distance") are far more likely to be chosen for inclusion in optimal portfolios than stocks with larger stimulus-ideal point "distances." Only individuals PC-5, PC-6, PC-13, and PC-14 show more than minor deviations from the predicted investment behavior. Table 29 shows that, for most individuals, the average stimulus-ideal point distance for selected stocks is significantly lower than the average distance for stocks not selected by the portfolio managers. Once again, the "Phase III" utility function was found to provide the best representation of the preference patterns of the PM-chemical respondents. This is consistent with earlier results for both security analyst groups.

2. Group Spaces

The coordinates of the PM-chemical group space from earlier INDSCAL calculations were combined with individual preference rankings to form a "joint space" which contains a unique ideal point for each PM-chemical respondent. The results of this procedure are shown in Table 30. It appears that this initial step in summarization has caused a significant loss of accuracy in the relationship between stimulus-ideal point distances and the investment behavior of the portfolio managers. Virtually every individual now exhibits some degree of contradiction between his actual investment selections and his "predicted" choices derived from stimulus-ideal point distances.
<table>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>Phase</th>
<th>I</th>
<th>II</th>
<th>III</th>
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</thead>
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<td>3.03</td>
<td>3.97</td>
<td>3.74</td>
<td>4.57</td>
<td>1.87</td>
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<td>+</td>
<td>-</td>
</tr>
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<td>.41</td>
<td>-7.46</td>
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<td>-2.07</td>
<td>-4.94</td>
<td>1.38</td>
<td>-2.75</td>
<td>III</td>
<td>+</td>
<td>-</td>
<td>-</td>
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<td>-5.22</td>
<td>-4.60</td>
<td>-5.24</td>
<td>-5.46</td>
<td>-8.51</td>
<td>-0.03</td>
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<td>+</td>
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TABLE 28—Continued
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<th>Mean Distance: Non-selected Stocks</th>
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*Differences in means are statistically significant at $\alpha = .05$ level.*
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<th>PC-5</th>
<th>PC-6</th>
<th>PC-7</th>
<th>PC-8</th>
<th>PC-9</th>
<th>PC-10</th>
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</table>

*Note: The table represents the distances between stimulus and ideal points in a chemical group configuration space for various individuals and phases.*
TABLE 30--Continued

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<td>1.77</td>
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<td>6.46</td>
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<td>1.95</td>
<td>2.21</td>
<td>.09</td>
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<td>1.75</td>
<td>1.65</td>
<td>1.53</td>
<td>.25</td>
</tr>
</tbody>
</table>
Table 31 shows the mean stimulus-ideal point distances for selected stocks versus those not chosen for the portfolio managers' hypothetical portfolios. Although most of the distances show the hypothesized pattern, it can be seen that the significance of differences in means has been reduced somewhat through the use of the group configuration space in place of the individual joint spaces.

**Table 31**

**Portfolio Manager-Chemical Average Pref-Map Stimulus-Ideal Point Distances for Selected vs. Non-Selected Stocks (Group Configuration Space)**

<table>
<thead>
<tr>
<th>Individual</th>
<th>Mean Distance: Selected Stocks</th>
<th>Mean Distance: Non-Selected Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC- 1</td>
<td>10.67</td>
<td>13.18</td>
</tr>
<tr>
<td>PC- 2</td>
<td>-2.55</td>
<td>1.66*</td>
</tr>
<tr>
<td>PC- 3</td>
<td>-17.89</td>
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</tr>
<tr>
<td>PC- 4</td>
<td>-19.40</td>
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<td>19.48</td>
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<tr>
<td>PC- 6</td>
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<td>.88*</td>
</tr>
<tr>
<td>PC- 7</td>
<td>-1.08</td>
<td>3.38*</td>
</tr>
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<td>PC- 8</td>
<td>-3.55</td>
<td>-.03*</td>
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<td>PC-11</td>
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<td>-.54</td>
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<tr>
<td>PC-15</td>
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<td>.73*</td>
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</table>

*Differences in means are statistically significant at $\alpha = .05$ level.*
At the ultimate level of aggregation, the preference rankings for all portfolio manager-chemical respondents were summarized, resulting in a single "group ideal point" within PM-chem group configuration space. The "distances" between this ideal point and the common stock coordinates are shown as the "average" individual in Table 30. The rank ordering of these distances is shown in Table 32, along with rank orderings of group investment preference as measured by (a) number of times selected for a portfolio, and (b) total dollars "invested" by the portfolio managers in the various securities. The Spearman rank correlation coefficients between the group "distances" and the group preference indicators are .86 and .91, respectively, both significant at the $\alpha = .01$ level. This result indicates that the predictive validity of the PREF-MAP model continues to be quite high even at the portfolio manager group level.

Finally, the axis weightings from the PREF-MAP results in Figure 30 generally conform to the earlier axis-labeling results for the PM-chemical respondents. Dimension II, termed "generalized risk" in the earlier evaluation of Hypothesis 4, is weighted negatively by eleven of the fifteen portfolio managers. Dimension I, for which no suitable label was found in the earlier discussions, also shows a strong negative tendency, with ten respondents indicating a lack of preference for this characteristic. Finally, dimension III, which was labeled as a "return" axis in $H_4$, shows far fewer negative responses, with only three of the fifteen portfolio managers-chemical applying a negative weight to this group space dimension.
TABLE 32

PORTFOLIO MANAGERS—CHEMICAL PREFERENCE
RANKINGS OF STIMULUS COMMON STOCKS

<table>
<thead>
<tr>
<th>Stock</th>
<th>Distance Within Group Joint Space (1 = lowest)</th>
<th>Times Selected For Portfolio (1 = most)</th>
<th>Dollars Invested In Stock (1 = most)</th>
</tr>
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<tbody>
<tr>
<td>1. PPG</td>
<td>7</td>
<td>4 (tie)</td>
<td>5</td>
</tr>
<tr>
<td>2. Allied Chem.</td>
<td>8</td>
<td>9 (tie)</td>
<td>10</td>
</tr>
<tr>
<td>3. Diam. Sham.</td>
<td>10</td>
<td>9 (tie)</td>
<td>9</td>
</tr>
<tr>
<td>4. DuPont</td>
<td>3</td>
<td>2 (tie)</td>
<td>1</td>
</tr>
<tr>
<td>5. MMM</td>
<td>2</td>
<td>2 (tie)</td>
<td>3</td>
</tr>
<tr>
<td>6. Monsanto</td>
<td>4</td>
<td>4 (tie)</td>
<td>4</td>
</tr>
<tr>
<td>7. Dow</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>8. Celanese</td>
<td>5</td>
<td>6 (tie)</td>
<td>7</td>
</tr>
<tr>
<td>9. Union Carb.</td>
<td>6</td>
<td>6 (tie)</td>
<td>6</td>
</tr>
<tr>
<td>10. Comm. Solv.</td>
<td>11</td>
<td>6 (tie)</td>
<td>8</td>
</tr>
<tr>
<td>11. Koppers</td>
<td>9</td>
<td>11 (tie)</td>
<td>11</td>
</tr>
</tbody>
</table>

D: Portfolio Managers—Diverse

1. Individual Spaces

Table 33 shows the results of the PREF-MAP routine as applied to
the individual preference rankings and configuration spaces from earlier
MDS/SCAL calculations. With the bars in the body of the table indicating
those securities selected by each individual for his optimal portfolio,
it can be seen that the hypothesized relationship between stimulus-ideal
point distances and likelihood of selection is supported for most of the
portfolio managers. Only individuals PD-3 and PD-6 show more than minor
deviations from this pattern, and Table 34 shows that, while not
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<td>6.86</td>
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<td>3.27</td>
<td>0.90</td>
<td>2.31</td>
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<td>2.91</td>
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<td>1.17</td>
<td>6.08</td>
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<td>-7.22</td>
<td>-7.41</td>
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<td>- 4.76</td>
<td>- 3.55</td>
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<td>2.65</td>
<td>1.79</td>
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<td>2.13</td>
<td>6.33</td>
<td>III</td>
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<td>+</td>
</tr>
<tr>
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<td>1.69</td>
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<td>2.63</td>
<td>2.62</td>
<td>2.30</td>
<td>1.93</td>
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<td>+</td>
<td>-</td>
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<tr>
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<td>1.45</td>
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<td>6.62</td>
<td>7.36</td>
<td>III</td>
<td>+</td>
<td>-</td>
</tr>
</tbody>
</table>
statistically significant, the differences in the mean stimulus-ideal point distances between selected and non-selected stocks are in the proper directions. Thus, the increased diversity of the stimulus common stocks has had no apparent impact on the predictive validity of the individual joint space solutions. Also, as with earlier respondent groups, the Phase III utility model was used for all portfolio manager-diverse respondents as the best representation of individual preference patterns.

**TABLE 34**

**PORTFOLIO MANAGERS-DIVERSE AVERAGE PREF-MAP STIMULUS-IDEAL POINT DISTANCES FOR SELECTED VS. NON-SELECTED STOCKS (INDIVIDUAL JOINT SPACE)**

<table>
<thead>
<tr>
<th>Individual</th>
<th>Mean Distance: Selected Stocks</th>
<th>Mean Distance: Non-Selected Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD - 1</td>
<td>-54.39</td>
<td>-49.85*</td>
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<tr>
<td>PD - 2</td>
<td>-5.23</td>
<td>-.30*</td>
</tr>
<tr>
<td>PD - 3</td>
<td>2.15</td>
<td>2.98</td>
</tr>
<tr>
<td>PD - 4</td>
<td>.36</td>
<td>5.16*</td>
</tr>
<tr>
<td>PD - 5</td>
<td>-12.62</td>
<td>-7.95*</td>
</tr>
<tr>
<td>PD - 6</td>
<td>-1.29</td>
<td>-1.25</td>
</tr>
<tr>
<td>PD - 7</td>
<td>-9.91</td>
<td>-4.56*</td>
</tr>
<tr>
<td>PD - 8</td>
<td>1.01</td>
<td>6.16*</td>
</tr>
<tr>
<td>PD - 9</td>
<td>-.86</td>
<td>3.63*</td>
</tr>
<tr>
<td>PD - 10</td>
<td>-8.60</td>
<td>-4.27*</td>
</tr>
<tr>
<td>PD - 11</td>
<td>-7.99</td>
<td>-7.51</td>
</tr>
<tr>
<td>PD - 12</td>
<td>-5.69</td>
<td>-.87*</td>
</tr>
<tr>
<td>PD - 13</td>
<td>.42</td>
<td>5.45*</td>
</tr>
<tr>
<td>PD - 14</td>
<td>-2.53</td>
<td>-2.00*</td>
</tr>
<tr>
<td>PD - 15</td>
<td>-7.15</td>
<td>-1.78*</td>
</tr>
</tbody>
</table>

* Differences in means are statistically significant at $\alpha = .05$ level.
2. Group Spaces

When individual preference rankings are combined with the three-dimensional coordinates of the PM-diverse group space, the results are as shown in Table 35. This table contains the calculated distances between the individual ideal points and the common stock coordinates of the group configuration space. As was found with previous respondent groups, the placing of individual ideal points within the group configuration space had very little adverse impact on the predictive ability of the PREP-MAP joint space model. In fact, precisely the same three individuals whose investment behavior deviated somewhat from predicted patterns in the analysis of individual spaces are also seen in Table 35 not to conform to this distance vs. selection pattern when placed in the group configuration space. This result is highlighted in Table 36, which shows that average stimulus-ideal point distances for "selected" stocks are significantly below those for non-selected stocks for all the portfolio manager respondents except individuals PD-3, PD-6, and PD-11. This shows that little, if any, information has been lost through the combining of the similarity judgments of the entire portfolio manager-diverse group into a single group configuration space.

At the final level of summarization, which is the locating of a single "average" group ideal point within the PM-diverse configuration space, the predictive ability of the PREP-MAP model is still high. The stimulus ideal point distances for the "average" individual in Table 35 result in the hypothesized preference rankings for the common stocks shown in column 1 of Table 37. The calculated Spearman rank correlation coefficients between predicted investment preference (column 1) and subsequent investment "behavior" (columns 2 and 3) are .82 and .78,
<table>
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<th>Individual</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>Phase</th>
<th>Axis Weight</th>
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<tbody>
<tr>
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<td>4.99</td>
<td>5.70</td>
<td>4.26</td>
<td>2.04</td>
<td>1.39</td>
<td>0.17</td>
<td>3.42</td>
<td>0.42</td>
<td>7.98</td>
<td>0.25</td>
<td>III</td>
<td>+</td>
</tr>
<tr>
<td>PD- 2</td>
<td>1.20</td>
<td>0.66</td>
<td>1.26</td>
<td>3.52</td>
<td>0.52</td>
<td>1.81</td>
<td>1.13</td>
<td>4.85</td>
<td>0.18</td>
<td>3.32</td>
<td>4.29</td>
<td>III</td>
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<td>PD- 3</td>
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<td>0.76</td>
<td>3.26</td>
<td>3.88</td>
<td>2.81</td>
<td>3.16</td>
<td>1.52</td>
<td>3.18</td>
<td>0.05</td>
<td>2.54</td>
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</tr>
<tr>
<td>PD- 4</td>
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<td>6.80</td>
<td>0.57</td>
<td>1.05</td>
<td>1.25</td>
<td>2.28</td>
<td>7.09</td>
<td>2.06</td>
<td>2.37</td>
<td>2.02</td>
<td>III</td>
<td>+</td>
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<td>0.29</td>
<td>0.86</td>
<td>0.07</td>
<td>1.51</td>
<td>1.88</td>
<td>III</td>
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<td>PD- 6</td>
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<td>2.36</td>
<td>2.84</td>
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<td>0.85</td>
<td>III</td>
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<td>0.52</td>
<td>1.35</td>
<td>1.42</td>
<td>5.28</td>
<td>0.97</td>
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<td>PD- 8</td>
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<td>2.93</td>
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<td>1.62</td>
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<td>-7.01</td>
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<td>4.59</td>
<td>1.06</td>
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<td>III</td>
<td></td>
</tr>
</tbody>
</table>
respectively. These correlations, although statistically significant at the $\alpha = .05$ level, are less than the values achieved by the previous investor groups for this highest level of summarization. Thus, because of either increased diversity of opinion within the investor group, or because of increased diversity of the stimulus set itself, it appears that the PREF-MAP model is less successful in the construction of a large-scale predictive model for the PM-diverse respondents than it was for the other investor groups surveyed in this research.

**TABLE 36**

**PORTFOLIO MANAGERS-DIVERSE AVERAGE PREF-MAP STIMULUS-Ideal Point Distances for Selected vs. Non-Selected Stocks (Group Configuration Space)**

<table>
<thead>
<tr>
<th>Individual</th>
<th>Mean Distance: Selected Stocks</th>
<th>Mean Distance: Non-Selected Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD-1</td>
<td>-.05</td>
<td>4.73*</td>
</tr>
<tr>
<td>PD-2</td>
<td>-2.94</td>
<td>.79*</td>
</tr>
<tr>
<td>PD-3</td>
<td>1.70</td>
<td>2.86</td>
</tr>
<tr>
<td>PD-4</td>
<td>1.65</td>
<td>4.22*</td>
</tr>
<tr>
<td>PD-5</td>
<td>-2.18</td>
<td>.32*</td>
</tr>
<tr>
<td>PD-6</td>
<td>.48</td>
<td>1.62</td>
</tr>
<tr>
<td>PD-7</td>
<td>-1.39</td>
<td>3.02*</td>
</tr>
<tr>
<td>PD-8</td>
<td>-.84</td>
<td>2.83*</td>
</tr>
<tr>
<td>PD-9</td>
<td>.76</td>
<td>4.87*</td>
</tr>
<tr>
<td>PD-10</td>
<td>-.01</td>
<td>3.75*</td>
</tr>
<tr>
<td>PD-11</td>
<td>.63</td>
<td>2.11</td>
</tr>
<tr>
<td>PD-12</td>
<td>-.79</td>
<td>3.14*</td>
</tr>
<tr>
<td>PD-13</td>
<td>-6.02</td>
<td>-2.13*</td>
</tr>
<tr>
<td>PD-14</td>
<td>2.12</td>
<td>6.63*</td>
</tr>
<tr>
<td>PD-15</td>
<td>-.31</td>
<td>2.65*</td>
</tr>
</tbody>
</table>

* Differences in means are statistically significant at $\alpha = .05$ level.
<table>
<thead>
<tr>
<th>Stock</th>
<th>Distance Within Group Joint Space (1 = lowest)</th>
<th>Times Selected For Portfolio (1 = most)</th>
<th>Dollars Invested In Stock (1 = most)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IBM</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>S.O.N.J.</td>
<td>10</td>
<td>8 (tie)</td>
<td>8</td>
</tr>
<tr>
<td>A.T.&amp;T.</td>
<td>11</td>
<td>8 (tie)</td>
<td>9</td>
</tr>
<tr>
<td>Polaroid</td>
<td>5</td>
<td>5 (tie)</td>
<td>6</td>
</tr>
<tr>
<td>Avon</td>
<td>8</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Burroughs</td>
<td>1</td>
<td>2 (tie)</td>
<td>2</td>
</tr>
<tr>
<td>MMM</td>
<td>6</td>
<td>8 (tie)</td>
<td>10</td>
</tr>
<tr>
<td>TNA</td>
<td>9</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>Warn.-Lamb.</td>
<td>3</td>
<td>2 (tie)</td>
<td>3</td>
</tr>
<tr>
<td>Amer. Air.</td>
<td>7</td>
<td>5 (tie)</td>
<td>5</td>
</tr>
<tr>
<td>Sears</td>
<td>2</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

As a sidelight to the results discussed thus far, it might be noticed that every portfolio manager-diverse respondent selected IBM as one of the stocks in his hypothetical optimal portfolio. This behavior occurred regardless of the stated degree of preference for this stock (several placed it quite low when ranking securities by "investment preference") and irrespective of the stimulus-ideal point distance calculated for IBM in the "joint space" results. Apparently, no matter what their real feelings about the security, none of the portfolio managers-diverse could bring themselves to construct a hypothetical portfolio which did not include IBM.
Finally, the axis weightings in Table 35 conform to expected results based on the axis labeling conclusions discussed above under \( H_4 \). Dimension I, termed "long-term expected return" in earlier results, is weighted positively by thirteen of the fifteen PM-diverse respondents. Dimension III, which was tentatively labeled "liquidity" from subjective ranking data, shows similar results with eleven subjects providing positive weights to this axis. On the other hand, dimension II, labeled "investment risk" in \( H_4 \), shows a far higher predominance of negative weightings (eleven out of fifteen) than the other two axes, lending credence to the earlier interpretation of the nature of this evaluative dimension.

Chapter V presented the results of the attempt, through the use of multidimensional scaling and related analytical techniques, to construct accurate descriptive and predictive models of both individual and group investment behavior. Hypothesis 4 was concerned with assigning accurate "labels" to the dimensions of the three-dimensional configuration spaces constructed for each of the four respondent groups. Hypothesis 5 utilized individual and averaged "group" preference rankings to formulate predictive investment models whose predictions were compared to subjects' investment "behavior" in the construction of hypothetical portfolios.

Chapter VI will summarize the results of this research and the implications of its conclusions for the theory and practice of finance and investment management. In addition, some suggestions for further research along the lines of the work discussed in this dissertation will be presented.
CHAPTER VI

SUMMARY, IMPLICATIONS, AREAS FOR FUTURE RESEARCH

The primary purpose of this research is to increase the understanding of the way in which important investors, operating both as individuals and as members of larger groups, make common stock investment decisions. Such an understanding implies knowledge of the number of factors, the nature of important variables, and the ways in which these variables are used by individuals in the selection of one security over another. The search for this knowledge has led to the use of a group of techniques based on the concept of multidimensional scaling in order to formulate concise descriptive and predictive models of both individual and group investment behavior. Thus, a corollary objective of this research is the evaluation of MDS and related algorithms as tools for use in the modeling of investor perceptual patterns and the analytical determination of the nature and consistency across individuals of salient investment variables.

The following sections will summarize the important results and conclusions of this research, the implications of the results noted herein for the theory and practice of finance, and finally, some areas of potential future research along the lines described in this dissertation.

A: SUMMARY OF RESEARCH RESULTS

Hypothesis 1 was aimed at determining the dimensionality of individual perceptual patterns. It essentially asks the question of how many
salient variables are involved in the individual security investment decision process. Individual multidimensional scaling solutions were calculated for each of the sixty-two respondents from whom similarity-dissimilarity judgments were obtained. Examination of the Kruskal stress values for these individuals in spaces of varying dimensionalities showed that (a) a wide range of perceptual dimensionality existed among the respondents, and (b) for many individuals (approximately 80 per cent of those sampled) more than two dimensions were required to represent accurately the perceived similarities between various pairs of common stocks. In fact, nearly three out of four of the security analyst and portfolio manager respondents surveyed in this research required configuration spaces of either three or four dimensions before the Kruskal stress measure fell below .10 (the level required for an "excellent" fit between configuration interpoint distances and the original similarity judgments).

Within the specific investor groups surveyed in this research, a variety of perceptual dimensionalities appeared. The chemical analyst individuals generally exhibited the fewest salient dimensions in their perceptual patterns, while the portfolio managers-chemical required the most. The "average" individual in both the chemical analyst and the portfolio manager-diverse group achieved an "excellent" fit (i.e., Kruskall stress below .10) in spaces of three dimensions. The "average" non-chemical analyst and PM-chemical individual required four dimensions before excellent fits were achieved.

Hypothesis 2 was concerned with identifying the significance of perceptual differences between the four respondent groups. Two different approaches, employing both the Tucker-Messick "VIEWS" individual
differences model and the Ward Hierarchical Clustering routine, were used to identify and measure the significance of variations in perceptual patterns. The results of these two techniques were generally supportive of each other. The perceptual patterns of the two security analyst groups (chemical and non-chemical analysts) were found to be quite different, a fact attributed to the difference in amounts and sources of information available to the chemical analyst respondents. Attempts to identify differences in perception due to an individual's "investment context" by looking at the perceptual patterns of security analysts vs. those of portfolio managers regarding an identical list of chemical stocks were generally inconclusive, although PM-chemical respondents held generally similar points of view to those of the non-chemical security analysts. Finally, in the attempt to identify perceptual differences due to variations in the nature of the stimulus securities, the similarity judgments gathered from two portfolio manager groups (PM-chemical and PM-diverse) were examined. Both analytical techniques confirmed differences in perceptual viewpoints between the two groups by forming clusters of individuals on the basis of similarity judgments whose members corresponded perfectly to the original portfolio manager respondent groups. In summary, significant differences were identified in the perceptual patterns of the two security analyst groups (reason: information levels) and between the two portfolio manager groups (reason: nature of the stimulus set). No conclusive modifications in perceptual patterns due to the "context" in which investment decisions are made could be identified.

Hypothesis 3 was concerned with the extent to which the respondent groups sampled in this research can be considered homogeneous in terms
of the manner in which they perceive similarities among the stimulus securities. Both the Tucker-Messick VIEWS program and the Ward Hierarchical Clustering routine were used to examine the four original investor groups for significant subgroups or "clusters" of individuals with distinct "points of view." Although both techniques identified some smaller groupings of individuals with similar perceptual patterns, it was concluded that none of these clusters were sufficiently large or homogeneous themselves to motivate further analysis on an inter-cluster basis rather than on the basis of the previously defined investor groups. Thus, the perceptual patterns of the individuals within the four respondent groups were considered to be sufficiently homogeneous to allow subsequent testing and analyses to be performed on a single unique configuration space for each of the four original respondent groups.

The purpose of the efforts under Hypothesis 4 was to provide precise axis labels for the dimensions of the group configuration spaces defined via the INDSCAL program. The PROFIT axis labeling program was used in this effort along with property vectors derived both from respondents' subjective ratings of the common stocks and from objective return, risk, and growth measures calculated from historical data. For each of the four respondent groups, both a "return" axis and a "risk" axis were tentatively identified, although precise statistical "labels" were, at times, not assigned to these dimensions. This was generally due to the presence of several potential labels which were highly correlated with each other and which were, therefore, largely indistinguishable when located in the configuration spaces. Of interest was the identification of "dividend yield" dimensions in the configuration spaces of both security analyst groups, and the fact that, with the
exception of the GM-chemical group, tentative axis labels were generally
drawn from the long-term (subjectively estimated or objectively calcu-
lated) property vectors. Only the portfolio manager-chemical group
appeared to be strongly influenced by the short-term risk and return
characteristics of the stimulus common stocks.

Finally, the objective of Hypothesis 5 was the construction and
validation of predictive security selection models for both individuals
and for the four respondent groups. For this purpose, the Carroll-
Chang PREF-MAP program was used with preference data gathered from re-
spondents to locate individual ideal points within the unique individual
configuration spaces and within the "group" configuration spaces con-
structed under Hypothesis 4. Security preference predictions based on
these PREF-MAP results were found to be highly correlated with the
subjects' subsequent investment "behavior" in the construction of
"optimal" portfolios from the list of stimulus common stocks. Even the
calculation of an "average" ideal point for all individuals in a given
group space provided predictions of group investment preference which
were highly (and significantly) correlated with summary measures of
subsequent group investment activity.

This discussion has summarized the results and the conclusions
drawn from the research described in Chapters III, IV, and V. Both
the results and the techniques used in this research to gain a better
understanding of the way individuals make investment decisions contain
certain implications for finance theory, practice, and research
methodology. These considerations will be the subject of the following
section.
B: IMPLICATIONS OF RESEARCH RESULTS

An entire generation of investment management and capital market theory has been developed based on the normative portfolio selection model first proposed by Markowitz. From this foundation have come the portfolio selection, portfolio evaluation, capital asset pricing, and cost of capital (theory of the firm) models of Sharpe, Lintner, Jensen and many others; models which have formed the basis for the major developments in finance theory during the past decade. Furthermore, many of these models have been tested empirically, with varying degrees of success, for their ability to provide insights into the interactions of financial variables in "real world" financial decision situations.

Whether or not one perceives a declining marginal utility in the proliferation of financial models based on normative assumptions, it would appear that there is as much, if not more to be gained in the understanding of the finance "world" from the construction and analysis of descriptive models of investment behavior as from the attempted molding of normative models into descriptive forms. In essence, the question "How do investors select stocks?" appears just as important as "How should investors select stocks?" Furthermore, if the answers to these two questions are different, then the importance of the development of a new generation of capital market and portfolio selection models based on accurate descriptive models of investor behavior is increased.

The results of the research described in earlier chapters have shed considerable light on the perceptual and investment behavior patterns of important groups of market participants. These results have pointed out several areas in which the ways in which investors
actually make investment decisions differ from or contain important implications for the capital asset pricing and portfolio evaluation models derived from normative assumptions.

The first major results of this research with implications for the current state of financial theory involved the number of salient attributes utilized by respondents in their judgments of similarity between pairs of common stocks. Nearly eighty per cent of the respondents exhibited perceptual spaces of either three or four dimensions; a result clearly at odds with the well-known two-dimensional normative portfolio selection and capital market models. Regardless of the nature of the variables used, it would appear that the two-dimensional models can never totally reflect all the varied aspects and intricacies of the ways in which a security's characteristics or investor estimates thereof are translated into investment decisions and conditions within capital markets. Although a few authors have extended normative portfolio selection models to more than two dimensions, these efforts primarily involve consideration only of the higher-order moments of stock price distributions, while ignoring many of the "non-statistical" variables (liquidity, quality of management, earnings growth) identified in this research as salient considerations for important investor groups. In summary, by basing market and portfolio theory on the narrower normative models of investor behavior, it is possible that the robustness and diversity of the influences within our system of capital markets has been hidden, resulting in theories and models of investment, portfolio evaluation, and capital market operations which contain inevitable inaccuracies.
A second aspect of current capital market theories whose accuracy must be questioned based on the results of this research is the assumption that all investors utilize the same criteria in their evaluation of the risk and return characteristics of common stocks. It is true that, for all four investor groups surveyed in this research, it was possible to identify perceptual dimensions relating to both the return and risk characteristics of the stimulus securities. However, subsequent axis labeling efforts pointed out that substantial variations existed in the nature of these risk and return perceptions. Within the chemical analyst group, the only return axis identified was expected dividend yield (subsequently weighted negatively) while for the non-chem analysts, an additional "generalized return" axis was identified in addition to the dividend yield dimension. The portfolio manager-chemical respondents exhibited a strong concern about the short-term risk and return characteristics of stocks, while the other group axes were generally associated with long-term (subjective or objective) risk and return variables. In essence, the significant differences which were identified between the risk and return perceptions of the various respondent groups refute the assumptions of current market models which utilize single measures of risk and return to represent the perceptions of all investors. Furthermore, these results cast serious doubts on the feasibility of constructing accurate large scale descriptive or predictive investment models for diverse groups of market participants.

In a related sense, this diversity of opinion or viewpoints of the salient features of security evaluation could at least partially explain the lack of success which has been achieved in the prediction of security price movements through the use of regression techniques.
These regression approaches, summarized and critiqued so ably by Keenan, would suffer in terms of accuracy and explanatory ability if the saliences of the various predictor variables differed between important investor groups.

Two additional potential implications of this research, although admittedly hypothetical, must be considered at this time. The first deals with the Random Walk Hypothesis, and specifically with the development of security selection models which would enable an investor to consistently "outperform the market" over extended time periods. It would appear possible that, if predictive models of the type described in Chapter V were constructed for influential investor groups (i.e., mutual fund managers, pension fund trustees, other institutional investors, etc.) it would be possible to make predictions, at a given point in time, about the relative attractiveness of various securities within the broad list of potential investment alternatives available to these investors. Furthermore, assuming subsequent investment behavior is positively correlated with these preference ratings, the potential exists for the identification or selection of stocks which would perform better than the list as a whole. Continuous monitoring of securities would be required, however, in order to observe movements toward or away from the group ideal point, or to track movements of the ideal point itself.

Finally, since the "ideal point" is assumed to represent that combination of attributes which is most highly preferred by investors, it would appear that the potential exists for increasing the value of the firm (or, conversely, lowering the firm's cost of capital) by the

proper tailoring of corporate investment and capital budgeting policies. This would involve selecting that mix of investments whose impact on company results would correspond most closely with the characteristics of the ideal points within the "joint spaces" of important investor groups for the company's securities.

Several of the potential impacts on current finance theory noted above are admittedly speculative. However, they do point out the directions which a new generation of finance theory, based on descriptive models of investor behavior, might eventually take. Thus, the primary result of this dissertation is the identification of significant differences between the current body of capital market and portfolio selection theory based on normative assumptions, and the conclusions reported in previous sections about the ways important investor groups actually make investment decisions. The most significant implication of this result is the need for the development of a new series of financial models based on accurate descriptive models of investor behavior. On a slightly less ambitious level, further research into actual investor decision processes could direct the formulation of normative portfolio selection and capital asset pricing models along lines more consistent with actual patterns of investor behavior. Finally, the success of multidimensional scaling and related techniques in the construction of the descriptive and predictive models of this research implies that such approaches should continue to be developed and applied to the study of finance in general and to the investment process in particular.

C: AREAS FOR FURTHER RESEARCH

As noted earlier, except for an article by Green and Maheshwari, this research represents the first systematic application of
multidimensional scaling and its related techniques to the study of the individual investment selection process. As such, this work provides not only new information about investment behavior, but also lessons and insights into the ways MDS techniques could be more properly and efficiently utilized in subsequent research into similar or related problems in the areas of finance and investment management. The following discussion, therefore, will be divided into two parts. First, certain comments will be provided about ways in which further research concerned specifically with the hypotheses discussed in this dissertation might be carried out. In a sense, this will be a look with "20-20 hindsight" at the methodologies employed during the course of this dissertation. The second part of this final section will be devoted to outlining possible extensions of the research discussed earlier and describing the nature of possible follow-up studies to this dissertation; efforts which would not only amplify and refine the conclusions of this research, but broaden our understanding of both investment behavior and the most useful and efficient techniques for probing and modeling it.

Several comments should be made about various aspects of the research methodology utilized in this dissertation. The first concerns the list of common stocks used as stimuli for the generation of similarity-dissimilarity judgments and preference rankings. It appears possible that the two groups of securities used as stimuli in this research were not drawn from a wide enough spectrum in terms of their investment nature and characteristics to cause the full range of variables used by individuals in investment decisions to be brought into play through the similarity judgments. This possibility is certainly
evident in the case of the list of eleven stocks drawn from the chemical industry, but such an argument might be made for the "diverse" stocks as well. In this case, in the effort to insure the familiarity of the respondents with the stimulus securities, large institutional favorites from "Wickers' Favorite Fifty" formed the sample from which eleven stocks were randomly selected. It seems possible that certain characteristics, such as investment risk, growth in sales and earnings, and dividend yield might have been distinguished more easily in the axis-labeling attempts if lower quality securities or stocks with a wider range of investment qualifications had been included for consideration in the lists of stimulus securities.

In terms of respondent selection, with the relatively limited universe of security analysts and portfolio managers from whom responses could be obtained, it is concluded that the "pre-contact" of prospective respondents was essential in insuring a representative number of responses from the various investor groups as well as the conscientious completion of the rather long and detailed questionnaire. For larger investor groups, it is possible that random sampling and mass questionnaire distribution techniques could provide adequate data for obtaining insights into the nature of group perceptual patterns.

In terms of the questionnaire construction itself, the basic data utilized in this study was similarity-dissimilarity judgments, a preference ranking of the eleven stimulus stocks, subjective ratings of the stocks on a variety of potentially important investment variables, and a hypothetical "optimal" portfolio constructed from the stimulus securities. If axis labeling is to be attempted using only statistical property vectors, the subjective estimates noted above would not be
required, and a single questionnaire could be used. If, however, labeling on the basis of subjective rankings is to be attempted, it is recommended that separate questionnaires (separated by a brief time interval) be employed to insure that all the perceptual, preference, and ranking data which is obtained really represents respondents' best estimates of these characteristics and not inaccurate judgments caused by haste or fatigue. As a final note on questionnaire construction, recent Monte Carlo simulation studies by Klahr which investigated the interaction between numbers of stimuli, configuration dimensions, and Kruskal stress values have indicated that, for the number of significant dimensions apparently exhibited by most individuals in making security evaluations, stimulus set sizes of at least 9-10 common stocks are required before low Kruskal stress values can be assumed to be caused by other than mathematical inevitability.\(^2\)

In terms of the evaluation of the hypotheses of this research, several lessons were learned which might make future efforts along these lines more productive and efficient. First, as a broad observation, it appears that, depending on the research objectives, the large amount of individual analyses performed in this study may not be necessary for the understanding of the investment decision process. Results noted earlier have shown that, in general, the perceptual patterns of individuals within the four respondent groups sampled were largely homogeneous, allowing the aggregation of individual similarity data into single "group" configuration spaces. Furthermore, individual investment behavior can be predicted nearly as accurately through the locating of

\(^2\)David Klahr, "A Monte Carlo Investigation of the Statistical Significance of Kruskal's Non-Metric Scaling Procedure."
idiosyncratic ideal points within the group space as can be done with the individual spaces constructed for each subject. Thus, unless the researcher is specifically interested in the pattern of individual perceptual dimensionalities, the construction of a separate configuration space for each respondent will, in most instances, be a highly inefficient and probably superfluous exercise.

In the efforts to identify perceptual differences between respondent groups as well as homogeneous "clusters" of individuals within the groups themselves, two separate techniques were employed. One was the Tucker-Messick "VIEWS" individual differences model; the other was the Ward Hierarchical Clustering routine. Although the results obtained from both models were largely duplicative of each other, the Ward routine appeared to be the more satisfactory approach to the identification of clusters of individual "points of view." Although processing time was higher (including the use of normalization and interpretive computer programs), the Ward output contains, in a concise, visual format, information about the numbers of important clusters, their "significance" (measured by reduction in E.S.S.), and the specific respondents who comprise the various groupings. The Ward technique appears to be a more complete and efficient model for the identification of respondent "clusters" than the Tucker-Messick "VIEWS" program.

The area of this dissertation in which results were felt to be the least conclusive was that of axis labeling. Although the nature of most of the axes within the four group configuration spaces could be inferred, only partial success was attained in providing explicit statistical labels to these dimensions. Subsequent efforts in this area might benefit from the following modifications to the methodology used
in this research. First, less effort might be expended in the calculation of various statistical risk and return measures. These variables were found to be generally quite highly intercorrelated, resulting in property vectors so closely aligned within the configuration spaces as to be largely indistinguishable from one another. Just two or three each of the return and risk variables should be sufficient to identify and provide satisfactory labels for dimensions of this nature within the group spaces. Second, certain additional statistical variables should be included in future efforts of this kind which were overlooked during this research. Of special interest would be the calculated $B$ coefficients for the stimulus set, as well as measures of historical dividend yield (especially for security analyst individuals) and perhaps additional measures of earnings or stock price growth. If a large number of statistical variables are being utilized, a factor analysis approach might be useful to construct linearly independent "pseudo-variables" which could be located in the space, then, for those providing acceptable axis labels, related back to one or a small group of the original statistical variables.

In terms of the providing of acceptable subjective labels to group space dimensions, it appeared that a wider range of attributes might be required before identification of all salient investment dimensions can be made. This problem is tied not only to the skill of the researcher in identifying possible "candidates" for axis labels, but also to the matters of questionnaire size and the ability of the respondents to provide meaningful rankings of securities on many different investment attributes. In addition, the assumption of the uniqueness and "meaningfulness" of the dimensions located by the INDSCAL program is a question
which deserves further consideration and, hopefully, experimental confirmation.

Finally, as noted earlier, the results of this research have indicated that individual configuration spaces are not essential to the construction of accurate individual predictive security selection models. The requirement for the construction of individual perceptual spaces in future research of this type appears, therefore, to be a function of the objectives of the research itself, and not a necessity in order to obtain satisfactory individual preference models.

Although the comments provided above are concerned with modifications and improvements which could be made in subsequent research efforts along the lines discussed in previous chapters, the basic approaches and MDS-related techniques described throughout this dissertation appear to have been successful in the evaluation of the research hypotheses constructed in Chapter I. The results described in this research have demonstrated the accuracy and the efficiency with which individual perceptual and preference patterns can be modeled and predicted. It appears that multidimensional scaling and its related computer algorithms (MDSCAL, INDSCAL, PREF-MAP, PROFIT, etc.) represent powerful tools in the hands of researchers interested in understanding, modeling, and predicting the complex behavior called "investing." With this conclusion, certain extensions and areas for future research along the lines of the work begun in this dissertation can be outlined.

First, it is apparent that more studies are required which are aimed explicitly at the identification of the salient investment attributes of important investor groups. Studies aimed solely at the labeling of important perceptual dimensions should be expanded to
different groups or replicated over varying time horizons, investment situations, market stages, etc. Corollary studies could focus more directly on the ways in which varying information or the kinds of information received can modify individual or group perceptual patterns.

A second important area for further research lies in studies aimed at broadening the evaluation and utilization of the "joint space" predictive models of investor behavior constructed in this dissertation. In terms of the evaluation of predictive models of this type, a more thorough methodology than was used in this research might involve the constructing and labeling of the axes of a "joint space" on the basis of judgments about one set of stocks, then testing the predictive accuracy of this model on a separate list of stimulus securities. This would involve comparing the calculated stimulus-ideal point distances for the new set of securities after being located as configuration points within the joint space with observed measures of investment preference or behavior gathered outside the context of the research itself. If it is found possible to make predictions about the relative investment preferences of large groups of individuals over large samples of stocks, then the ultimate step along these lines would be the attempt to correlate investment returns from securities over some time period with the relative degree of preference for this sample of stocks predicted by the joint space model. Such studies would lead to models aimed at "heating the market" by identifying those securities which are most likely to be favored by important investor groups in future security or portfolio selection decisions.

Finally, a great deal of potential for future work lies in the area of improving the MDS methodology itself. As noted earlier, the
importance of "group space" results in the formulation of large scale
descriptive or predictive models requires that the INDSCAL assumptions
concerning the uniqueness of its dimensional location need to be examined
closely. Perhaps even more important is the need for the development of
trustworthy "significance" measures for many of the MDS-related statisticss used in research of this type. These statistics include Kruskal
stress measures, property vector correlations, and results of clustering
calculations. Too much subjectivity remains in these areas in the de-
termination of the meaningfulness of calculated results. Finally, from
a purely technical viewpoint, many of the computer programs which per-
form the MDS-related computations are sadly out of date and require
extensive modification before they are suitable for use on many of the
newer computer systems. In addition, written documentation and instruc-
tions for several of the programs utilized in this research are practi-
cally nonexistent. If, as suspected, the use of multidimensional scaling
and related techniques is about to enter a period of rapid increase
within the business community, some effort should be made to upgrade
these programs and their documentation, as well as to centralize their
distribution. This would prevent future researchers in this area from
spending valuable time replicating previous efforts in the search for,
modification, and interpretation of numerous multidimensional scaling
computer programs.
APPENDIX A
Ohio State University
Finance Research Project
Chemical Questionnaire

This questionnaire is part of an Ohio State University Finance Research Project concerned with the way in which individuals perceive similarities or differences among the common stocks of large chemical companies.*

The following list of chemical stocks is being studied:

1. Pittsburgh Plate Glass (PPG)
2. Allied Chemical
3. Diamond Shamrock
4. E. I. DuPont deNemours (DuPont)
5. Minnesota Mining & Manufacturing (3M)
6. Monsanto
7. Dow Chemical
8. Celanese
9. Union Carbide
10. Commercial Solvents
11. Koppers Company

The purpose of this questionnaire is to obtain from each of you measures of the degree of relative similarity which you feel exists between various pairs of the common stocks listed above. Keep in mind that your preferences for the various stocks are not of importance here. Furthermore, it does not matter whether or not you actually own or have ever invested in any of the companies or stocks in the sample. We simply want your impressions of how much one common stock is like another in terms of its investment characteristics.

*All responses will be held in strict confidence. No support is being received from the chemical industry or the chemical companies listed—the industry and company selection was random.
On the following pages you will be presented with various pairs of common stocks drawn from the list of companies presented on the preceding page (some names have been abbreviated for space consideration). Please indicate how similar or how much alike you believe each pair of investment alternatives are by:

(a) circling 1 if you think they are very similar,
(b) circling 9 if you think they are very dissimilar, or
(c) choosing some number in between depending on how much alike you believe the investment choices are (circle only one number for each pair of stocks).

Remember, it does not matter what criteria you use to make your "similarity" ratings. We only ask that you attempt to be consistent in your judgments.

Please turn the page and begin.
<table>
<thead>
<tr>
<th>Similar</th>
<th>Dissimilar</th>
</tr>
</thead>
<tbody>
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<td>1. DuPont - Union Carbide</td>
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<td>2. Monsanto - Union Carbide</td>
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<td>3. Dow Chemical - Monsanto</td>
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<td>5. Minn. Min. &amp; Manuf. (3M) - Koppers Comp.</td>
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<td>7. Monsanto - Commercial Solvents</td>
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<td>11. Union Carbide - Pittsburgh Plate Glass (PFG)</td>
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<td>12. Pittsburgh Plate Glass (P2G) - Allied Chemical</td>
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<td>14. Koppers Comp. - Allied Chemical</td>
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<td>15. Commercial Solvents - Union Carbide</td>
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<td>16. Diamond Shamrock - Pitts. Plate Glass (PFG)</td>
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<td>18. Diamond Shamrock - Koppers Comp.</td>
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<td>20. Commercial Solvents - DuPont</td>
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<td>23. Celanese - Allied Chemical</td>
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<td>24. Dow Chemical - Union Carbide</td>
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<td>Dow Chem. - Pitts. Plate Glass (PPG)</td>
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<td>Celanese - Koppers</td>
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<td>53.</td>
<td>Dow Chemical - Koppers</td>
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<tr>
<td>55.</td>
<td>DuPont - Pitts. Plate Glass (PPG)</td>
</tr>
</tbody>
</table>
Please list the criteria you feel you utilized in making your similarity judgments in the first section of this questionnaire.

1. 

2. 

3. 

4. 

Assume that you were asked to evaluate the relative investment merit under today's market conditions of each of the chemical stocks named earlier. Please rank this list of stocks from 1 to 11, beginning with that stock (rank = 1) which you consider to be the most desirable investment alternative on the list, and continuing (rank, 2, 3, 4, etc.) until you reach the stock you would least prefer (rank 11) as an investment under current conditions.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Company</th>
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<tbody>
<tr>
<td>1</td>
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<td>Minnesota Mining &amp; Manufacturing</td>
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<td>Monsanto</td>
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<td>9</td>
<td>Union Carbide</td>
</tr>
<tr>
<td>10</td>
<td>Commercial Solvents</td>
</tr>
</tbody>
</table>
In making a decision to buy or sell (or recommend the purchase or sale of) a common stock, some attributes of the security or characteristics of the company itself might be more important than others to you. Please indicate how important each of the following attributes is to you by:

(a) circling a lower number the more important an attribute is to you, or

(b) circling a higher number the less important an attribute is in your investment decisions (circle one number for each attribute).

1. Expected growth in earnings per share in the next 12 months
   1 2 3 4 5 6 7

2. Total expected return over the next 12 months (dividends plus price appreciation)
   1 2 3 4 5 6 7

3. Expected investment risk during the next 12 months
   1 2 3 4 5 6 7

4. Expected dividend yield over the next 12 months
   1 2 3 4 5 6 7

5. Expected growth in earnings per share over the next 3-5 years
   1 2 3 4 5 6 7

6. Total expected returns (dividends plus appreciation) over the next 3-5 years
   1 2 3 4 5 6 7

7. Expected investment risk during next 3-5 years
   1 2 3 4 5 6 7

8. Expected 3-5 year dividend yield
   1 2 3 4 5 6 7

9. Liquidity (ability to buy or sell large blocks quickly, near current market)
   1 2 3 4 5 6 7
Please list any other attributes of a company or its securities which strongly influence your investment decisions (these may include any factors unique to chemical industry investment decisions).

1. 

2. 

3. 

4. 

Assume you hold $10 million in cash which you have decided to commit to stocks in the chemical industry; specifically among the eleven chemical stocks in the sample. Please indicate below the order in which you would select stocks from this list for inclusion in your hypothetical portfolio, and the dollar amount you would invest in each stock. Please "use up" the entire $10 million, but feel free to choose as few or as many stocks from the list as you desire (i.e., you may "concentrate" or "diversify" your funds in any manner you please).

<table>
<thead>
<tr>
<th>Stock selected first</th>
<th>Name</th>
<th>$ Amount Invested</th>
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</thead>
<tbody>
<tr>
<td>Stock selected second (if any)</td>
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<td>Stock selected third (if any)</td>
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<td>Stock selected ninth (if any)</td>
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<td>Stock selected tenth (if any)</td>
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<td>Stock selected eleventh (if any)</td>
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</tbody>
</table>
Finally, please check the appropriate responses to the questions listed below:

1. What is your age?
   ___ 20-25
   ___ 26-35
   ___ 36-45
   ___ 46-55
   ___ 56-65
   ___ over 65

2. How many years have you been in the investments or securities business?
   ___ 0-3
   ___ 4-10
   ___ 11-15
   ___ 16-25
   ___ 36-40
   ___ over 40

3. Do you work for a:
   ___ brokerage firm
   ___ mutual fund
   ___ pension fund
   ___ bank trust department
   ___ other (specify)

4. Briefly, what are the investment objectives of the institution for which you work?

   ______________________________________________________
   ______________________________________________________
   ______________________________________________________

5. What kind of stock market performance do you foresee for the chemical industry over the next 12 months?
   ___ better than Dow Jones Industrial Average
   ___ about the same as the Dow Jones Industrial Average
   ___ worse than the Dow Jones Industrial Average

6. Where do you think the Dow Jones Industrial Average will be in 12 months?
   ___ higher than today
   ___ about the same as today
   ___ lower than today
APPENDIX B

Ohio State University
Finance Research Project
Investment Questionnaire

This questionnaire is part of an Ohio State University Finance Research Project concerned with the way in which individuals perceive similarities or differences among the common stocks of large industrial companies.*

The following diversified list of common stocks is being studied:

1. International Business Machines (IBM)
2. Standard Oil of New Jersey
3. American Telephone & Telegraph (AT&T)
4. Polaroid
5. Avon Products
6. Burroughs
7. Minnesota Mining & Manufacturing (3M)
8. Insurance Company of North America (INA)
9. Warner-Lambert Pharmaceuticals
10. American Airlines
11. Sears-Roebuck

The purpose of this questionnaire is to obtain from each of you measures of the degree of relative similarity which you feel exists between various pairs of the common stocks listed above. Keep in mind that your preference for the various stocks are not of importance here. Furthermore, it does not matter whether or not you actually own or have ever invested in any of the companies or stocks in the sample. We simply want your impressions of how much one common stock is like another in terms of its investment characteristics.

*All responses will be held in strict confidence. No support is being received from any of the companies listed above--the company selection was random.
On the following pages you will be presented with various pairs of common stocks drawn from the list of companies presented on the preceding page (some names have been abbreviated for space considerations). Please indicate how similar or how much alike you believe each pair of investment alternatives are by:

(a) circling 1 if you think they are very similar,
(b) circling 9 if you think they are very dissimilar, or
(c) choosing some number in between depending on how much alike you believe the investment choices are (circle only one number for each pair of stocks).

Remember, it does not matter what criteria you use to make your "similarity" ratings. We only ask that you attempt to be consistent in your judgments.

Please turn the page and begin.
<table>
<thead>
<tr>
<th>No.</th>
<th>Company 1</th>
<th>Company 2</th>
<th>Similar</th>
<th>Dissimilar</th>
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</thead>
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<td>1</td>
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<td></td>
<td>1 2 3 4 5 6 7 8 9</td>
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</tr>
<tr>
<td>3</td>
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<tr>
<td>4</td>
<td>Ins. Co. of North America - America Airlines</td>
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<td>5</td>
<td>Avon Products - Burroughs</td>
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<td>7</td>
<td>Sears - American Airlines</td>
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<td>Minn. Min. &amp; Manuf. - Polaroid</td>
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<td>51.</td>
<td>American Airlines - Polaroid</td>
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<td>1 2 3 4 5 6 7 8 9</td>
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<td>52.</td>
<td>American Airlines - Warner-Lambert</td>
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<td>53.</td>
<td>Avon - INA</td>
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<td>54.</td>
<td>Sears - Standard Oil (N.J.)</td>
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<td>55.</td>
<td>Warner-Lambert - INA</td>
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<td>1 2 3 4 5 6 7 8 9</td>
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Please list the criteria you feel you utilized in making your similarity judgments in the first section of this questionnaire.

1. 

2. 

3. 

4. 

Assume that you were asked to evaluate the relative investment merit under today's market conditions of each of the common stocks named earlier. Please rank this list of stocks from 1 to 11, beginning with that stock (rank = 1) which you consider to be the most desirable investment alternative on the list, and continuing (rank 2, 3, 4, etc.) until you reach the stock you would least prefer (rank 11) as an investment under current conditions.

Rank

1. International Business Machines (IBM).....................
2. Standard Oil of New Jersey..............................
3. American Telephone & Telegraph (AT&T)................
4. Polaroid..............................................
5. Avon Products........................................
6. Burroughs............................................
7. Minnesota Mining & Manufacturing (3M)................
8. Insurance Company of North America (INA)..............
9. Warner-Lambert Pharmaceuticals....................... 
10. American Airlines...................................
11. Sears-Roebuck......................................
In making a decision to buy or sell (or recommend the purchase or sale of) a common stock, some attributes of the security or characteristics of the company itself might be more important than others to you. Please indicate how important each of the following attributes is to you by:

(a) circling a lower number the more important an attribute is to you, or

(b) circling a higher number the less important an attribute is in your investment decisions (circle one number for each attribute).

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Important</th>
<th>Unimportant</th>
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<tr>
<td>1. Expected growth in earnings per share in the next 12 months</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>2. Total expected return over the next 12 months (dividends plus price appreciation)</td>
<td>1 2 3 4 5 6 7</td>
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<td>3. Expected investment risk during the next 12 months</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>4. Expected dividend yield over the next 12 months</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>5. Expected growth in earnings per share over the next 3-5 years</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>6. Total expected returns (dividends plus appreciation) over the next 3-5 years</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>7. Expected investment risk during next 3-5 years</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>8. Expected 3-5 year dividend yield</td>
<td>1 2 3 4 5 6 7</td>
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<tr>
<td>9. Liquidity (ability to buy or sell large blocks quickly, near current market)</td>
<td>1 2 3 4 5 6 7</td>
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</tbody>
</table>
Please list any other attributes of a company or its securities which strongly influence your investment decisions. These may include any factors or constraints imposed by the nature of the institution for which you make investment decisions.

1. 
2. 
3. 
4. 

Assume you hold $10 million in cash which you have decided to commit to stocks in the sample list we have considered previously. Please indicate below the order in which you would select stocks from this list for inclusion in your hypothetical portfolio, and the dollar amount you would invest in each stock. Please "use up" the entire $10 million, but feel free to choose as few or as many stocks from the list as you desire (i.e., you may "concentrate" or "diversify" your funds in any manner you please).

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<tr>
<th>Stock selected first</th>
<th>Name</th>
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<td>Stock selected second (if any)</td>
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<td>Stock selected eleventh (if any)</td>
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Finally, please check the appropriate responses to the questions listed below:

1. What is your age?
   ■ 20-25
   ■ 26-35
   ■ 36-45
   ■ 46-55
   ■ 56-65
   ■ over 65

2. How many years have you been in the investments or securities business
   ■ 0-3
   ■ 4-10
   ■ 11-15
   ■ 16-25
   ■ 36-40
   ■ over 40

3. Do you work for a:
   ■ brokerage firm
   ■ mutual fund
   ■ pension fund
   ■ bank trust department
   ■ other (specify)

4. Briefly, what are the investment objectives of the institution for which you work.

   ___________________________________________________________
   ___________________________________________________________
   ___________________________________________________________

5. Where do you think the Dow Jones Industrial Average will be in 12 months?
   ■ higher than today
   ■ about the same as today
   ■ lower than today
APPENDIX C

Ohio State University
Finance Research Project
Follow-Up Questionnaire

This OSU Finance Research Project questionnaire is concerned with individuals' expectations about the future performance of a specified list of common stocks.* Specifically, we will consider the following list of chemical industry common stocks:

1. Pittsburgh Plate Glass (PPG)
2. Allied Chemical
3. Diamond Shamrock
4. E. I. DuPont deNemours (DuPont)
5. Minnesota Mining & Manufacturing (3M)
6. Monsanto
7. Dow Chemical
8. Celanese
9. Union Carbide
10. Commercial Solvents
11. Koppers Company

The purpose of this questionnaire is to obtain from you a ranking of the eleven stocks listed above in terms of several attributes which are often considered important in making investment decisions. It does not matter whether or not a given attribute is important to you in evaluating investment alternatives; we simply want your best estimate of the relative ranking, from best to worst, of the stocks listed above in terms of several widely-used criteria.

*All responses will be held in strict confidence. No support is being received from any company listed above (company selection was random) or any other company or financial institution.
On the following two pages you will find a table which you may fill in to indicate your estimates of the future performance characteristics of the list of stocks discussed earlier. Down the left side of the table are listed several attributes or kinds of information about a company which might be utilized in making investment decisions. Please rank the companies listed across the top of the table from highest or best (rank = 1) to lowest or worst (rank = 11) in terms of each attribute by simply filling in the table, row by row. For instance, if you expect Monsanto to have the highest earnings growth during the coming year of all the companies listed, you would place a "1" in the first row under Monsanto. If you expect Union Carbide to have the next highest earnings increase, you would place a "2" in the first row under Union Carbide, and so on down the line through rank "11," the company with the lowest expected earnings growth over the next year. At this time, the entire first row will be complete. The same procedure should be followed for the remaining attributes. It is easiest to fill in completely one row at a time before moving on to the next investment attribute.

Please turn the page and begin.
## COMPANIES

Remember: best = 1  
worst = 11

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Remember: best = 1  
worst = 11
Finally, please check the appropriate responses to the questions listed below:

1. What is your age?
   - 20-25
   - 26-35
   - 36-45
   - 46-55
   - 56-65
   - over 65

2. How many years have you been in the investments or securities business?
   - 0-3
   - 4-10
   - 11-15
   - 16-25
   - 36-40
   - over 40

3. Do you work for a:
   - brokerage firm
   - mutual fund
   - pension fund
   - bank trust department
   - other (specify)
APPENDIX D

Ohio State University
Finance Research Project
Follow-Up Questionnaire

This OSU Finance Research Project questionnaire is concerned with individuals' expectations about the future performance of a specified list of common stocks.* Specifically, we will consider the following list of common stocks:

1. International Business Machines (IBM)
2. Standard Oil of New Jersey
3. American Telephone & Telegraph (A.T.&T.)
4. Polaroid
5. Avon Products
6. Burroughs
7. Minnesota Mining & Manufacturing (3M)
8. Insurance Company of North America (INA)
9. Warner-Lambert Pharmaceuticals
10. American Airlines
11. Sears-Roebuck

The purpose of this questionnaire is to obtain from you a ranking of the eleven stocks listed above in terms of several attributes which are often considered important in making investment decisions. It does not matter whether or not a given attribute is important to you in evaluation investment alternatives; we simply want your best estimate of the relative ranking, from best to worst, of the stocks listed above in terms of several widely-used investment criteria.

*All responses will be held in strict confidence. No support is being received from any company listed above (company selection was random) or any other company or financial institution.
On the following two pages you will find a table which you may fill in to indicate your estimates of the future performance characteristics of the list of stocks discussed earlier. Down the left side of the table are listed several attributes or kinds of information about a company which might be utilized in making investment decisions. Please rank the companies listed across the top of the table from highest or best (rank = 1) to lowest or worst (rank = 11) in terms of each attribute by simply filling in the table, row by row. For instance, if you expect Polaroid to have the highest earnings growth during the coming year of all the companies listed, you would place a "1" in the first row under Polaroid. If you expect Sears-Roebuck to have the next highest earnings increase, you would place a "2" in the first row under Sears-Roebuck, and so on down the line through rank "11," the company with the lowest expected earnings growth over the next year. At this time, the entire first row will be complete. The same procedure should be followed for the remaining attributes. It is easiest to fill in completely one row at a time before moving on to the next investment attribute.

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Remember: best = 1
worst = 11
Finally, please check the appropriate responses to the questions listed below:

1. What is your age?
   - 20-25
   - 26-35
   - 36-45
   - 46-55
   - 56-65
   - over 65

2. How many years have you been in the investments or securities business?
   - 0-3
   - 4-10
   - 11-15
   - 16-25
   - 36-40
   - over 40

3. Do you work for a:
   - brokerage firm
   - mutual fund
   - pension fund
   - bank trust department
   - other (specify)
APPENDIX E

FORMULAS FOR THE CALCULATION OF SELECTED OBJECTIVE RETURN
AND RISK MEASURES USED IN "PROFIT" AXIS LABELING
(HYPOTHESIS 4, CHAPTER V)

Let the Holding Period Return for a stock for month $T$ be defined as:

$$HPR_T = \frac{P_T - P_{T-1} + D_T}{P_{T-1}}$$

where

$P_T$ = Stock Price at end of month $T$

$D_T$ = Dividends Paid during month $T$

All the following measures were calculated for $N = 12$-month and $N = 60$-month periods preceding the time period of the questionnaire completion:

1. Arithmetic Average Month Return

$$A_{HPR} = \frac{\sum_{T=1}^{N} HPR_T}{N}$$

2. Geometric Mean Monthly Return

$$G_{HPR} = \left( \prod_{T=1}^{N} HPR_T \right)^{\frac{1}{N}}$$
3. Standard Deviation

\[
SD_{HPR} = \left[ \frac{1}{N} \sum_{T=1}^{N} (HPR_T - \overline{HPR}) \right]^{1/2}
\]

where \( \overline{HPR} = \frac{1}{N} \sum_{T=1}^{N} HPR_T \)

4. Coefficient of Variation

\[
CV_{HPR} = \frac{SD_{HPR}}{HPR}
\]

5. Semi-Standard Deviation

\[
SSD_{HPR} = \left[ \sum_{T=1}^{N} d_T^2 \right]^{1/2}
\]

where \( d_T = \begin{cases} (HPR_T - \overline{HPR}) & \text{if } (HPR_T - \overline{HPR}) > 0 \\ 0 & \text{if } (HPR_T - \overline{HPR}) \geq 0 \end{cases} \)

6. Modified Quadratic Mean

\[
MQM_{HPR} = \sum_{T=1}^{N} w_T^2
\]

where \( w_T = \begin{cases} (HPR_T - 1) & \text{if } (HPR_T - 1) < 0 \\ 0 & \text{if } (HPR_T - 1) \geq 0 \end{cases} \)

7. Log Deviation

\[
LD_{HPR} = \left[ \frac{1}{N} \sum_{T=1}^{N} (\log HPR_T - \overline{\log HPR}) \right]^{1/2}
\]

where \( \overline{\log HPR} = \frac{1}{N} \sum_{T=1}^{N} \log HPR_T \)
8. Mean Absolute Deviation

$$\text{MAD}_{HPR} = \frac{1}{N} \sum_{T=1}^{N} \left| (HPR_T - \overline{HPR}) \right|$$

As noted previously, all calculations were made for $N = 12$ and $N = 60$ (i.e., one-year and five-year time periods).
BIBLIOGRAPHY

JOURNAL ARTICLES


Kruskal, Joseph B. "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis." Psychometrika, XXIX (March, 1964), 1-29.


Young, Gale and Householder, A. E. "Discussion of a Set of Points in Terms of their Mutual Distances." Psychometrika, III (1938), 19-22.

BOOKS, PUBLISHED PROCEEDINGS


UNPUBLISHED MANUSCRIPTS, WORKING PAPERS, DISSERTATIONS


Chang, Jih-Jie, and Carroll, J. Douglas. "How to use PROFIT, a Computer Program for Property Fitting by Optimizing Nonlinear or Linear Correlation." Bell Telephone Laboratories, Murray Hill, New Jersey, March, 1969. (Mimeographed.)


Kruskal, J. B. "How to Use M-D-SCAL, A Program to do Multidimensional Scaling and Multidimensional Unfolding." Bell Telephone Laboratories, Murray Hill, New Jersey, 1968. (Mimeographed.)


