Effectiveness of Security Analyst Information Accessing Strategies: A Computer Interactive Assessment

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Abstract — The present study illustrates how computers can substantially extend the range and ease of application of the behavioral process information monitoring procedures that are increasingly being used to capture and preserve traces of pre-decision information accessing behavior. Employing such an extension, the study examined whether better and poorer decision maker performance was related to differences in the extent and content of information accessing behavior. The results of a computer simulation involving practicing financial security analysts engaged in a securities analysis task revealed that the better performing analysts generally considered slightly greater amounts of information and different types of information than did the poorer performing analysts. These findings are interpreted in terms of the concept of "control schemas" postulated by Kozminsky, Kintsch, and Bourne (1981). A concluding section describes numerous ways in which computers improve upon both the flexibility and validity of traditional research paradigms.

Human judgment and decision making have been the focus of considerable psychological theorizing and research. While generally conceptualized as dynamic processes, until recently, the empirical procedures used to study these processes

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failed to match, capture, or preserve this dynamism. The typical research paradigm involves relying on verbal reports collected either before or after the fact, and using such cross-sectional intentions and/or recall data as a basis for drawing inferences regarding what presumably happened during the processes themselves.

In contrast, the past two decades have seen the gradual emergence of various types of process methodologies. One such approach, termed verbal protocols, involves gathering a spontaneous top-of-the-mind running commentary from the individual as he or she engages in a decision making or judgment task. A second approach involves providing subjects with visual information displays and then tracking the sequence and duration of their eye movements and fixations in regard to these displays. The general assumption is that eye fixations correspond to information acquisition.

The third basic approach involves providing individuals with access to items of information in the external information environment and then monitoring the extent, sequence and content of the information which they selectively acquire from this environment. Though antecedents of behavioral process (BP) monitoring approaches surfaced earlier, the impetus for the increasing use of these procedures in consumer and organizational/human performance research stems from the work of Jacoby (Bettman & Jacoby, 1976; Jacoby 1975; Jacoby, Chestnut, Weigl & Fisher, 1976) and Payne (1976). Until recently, investigators employing these methods relied on some form of physical apparatus (usually termed an information display board) to store and display the available information. Such devices generally place severe limitations on the amount of information that can be contained in the external information environment and the ease and speed with which this information can be modified. They also permit the introduction of human error in the data recording process. Most recently, researchers are turning to interactive computer simulations as a means for dealing with these and other related problems.

The Information Context of Securities Evaluation

Finance scholars have conjectured that distinguishing between average and exceptional security analysts requires considering the manner in which these security analysts identify, acquire, interpret, and apply the available information (e.g., Bernstein, 1975, p. 58; Graham, Dodd, Cottle & Talham, 1966, p. 85). This hypothesis also surfaces in the writings of psychologists. For example, Slovic (1972) observes:

Security analysis, whether by expert or novice, might be labeled “The Information Game.” In no other realm are such vast quantities of information from such diverse sources brought to bear on so many important decisions. Careful accumulation and skilled interpretation of this information is said to be the sine qua non of accurate evaluation of securities. (p. 779)

A review of the literature reveals that much of the total variation in a particular firm’s stock prices can be attributed to factors that are unique to that company (as opposed to general market and industry factors) (Bernstein, 1975; Blume, 1971; Hagaman & Jensen, 1977, p. 64; King, 1966; Tersine & Celeg,
Such company-unique factors are often divided into those involving a specific company's financial statement (i.e., fundamental factors) and those which involve nonfinancial matters such as the quality of its management, or whether its labor force is about to negotiate a new contract. Prior research indicates that fundamental factors account for approximately 30% to 35% of the variance while other company-unique variables account for a total of 20% to 25% of the variance. Holding all other factors constant, this study examined how security analysts accessed or ignored fundamental factor information when arriving at "buy" recommendations. Recent psychological theorizing is relevant here.

Problem solving and decision making involve at least two basic processes such as information acquisition and information evaluation. Kozminsky, Kintsch, and Bourne (1981) postulate that the mental operations involved in both these processes are guided by cognitive control schemata—heuristics that individuals develop over time to guide the flow of information from the environment to and within the cognitive system. According to these theorists, better decision makers should be distinguishable from poorer decision makers by virtue of having developed more effective control schemata. The present investigation sought to identify quantity-, content-, and sequence-oriented control schemata operating during the information acquisition phase of security analyst decision making and to determine whether differences in these strategies would relate to differences in security analyst performance.

Prior Relevant Research

The most directly relevant investigations to date are those by Clarkson (1962), Slovic (1969), and Slovic, Fleissner and Bauman (1972). Clarkson attempted to identify the information used by a bank trust investment officer in his portfolio selection process. The investment officer was asked to "think aloud" while reviewing past and present decisions, and Clarkson collected a large number of protocols based on these verbalized reflections. The Slovic and Slovic et al. studies each examined ways in which security analysts weighed and combined information from diverse sources. Respondents were provided with fundamental factor information for a set of hypothetical companies. Based on this information, the task was to judge each company's growth potential over the next 6 to 18 months and arrive at a buy/no-buy recommendation.

Each of these prior studies suffered from a number of design shortcomings, many of which could have been rectified with the aid of computers. For example, given the tremendous amount of time and effort involved in collecting and analyzing verbal protocol data, Clarkson's (1962) study had to be confined to protocols generated by a single decision maker. There was no way of knowing whether this decision maker was typical of others, nor was there any way of con-

1A number of other design shortcomings existed as well (e.g., the use of hypothetical information for hypothetical companies rather than the actual information for real companies, the use of stock brokers and students as subjects rather than security analysts, the use of an imprecise and floating performance target that required subjects to predict security performance 12-18 months into the future). Space limitations preclude discussion of these issues here. Additional information is provided in a working paper available from the first author.
trasting effective with ineffective information accessing behavior or performance. The use of computers to collect, format, and analyze verbal protocol data could substantially reduce problems of this nature.

Likewise, difficulties associated with handling large quantities of data led Slovic (1969) and Slovic et al. (1972) to restrict their studies in a number of ways. First, while the real world environment facing security analysts confronts them with vast arrays of information, these studies were limited to only 11 and 8 items of fundamental factor information, respectively. The use of computers to store, organize, and present data to subjects should allow researchers to expand enormously the amount of information to which subjects can be exposed.

Second, the limited fundamental factor data that was presented to the subjects was categorical, rather than continuous, in nature. This meant that the subjects were exposed to information that was highly artificial. For example, describing the number of shares outstanding in a company as “few” versus “many,” or sales trends as “up” versus “down,” seriously violates the richness and variability of information found in the real world. The vast storage and data manipulation capacities of computers could help researchers overcome this problem by making it easier to present detailed, continuous data rather than artificially simplified categorical information.

Third, the lack of sophisticated data manipulation procedures resulted in exposing each subject to all the available information for each stock being examined. This is inconsistent with real-world decision making in which analysts attend only to those aspects of the information environment that interest them. Computer-assisted simulations can remove this problem by making available to subjects as much data as desired by the researcher and then allowing subjects to choose which pieces of data they would like to examine.

Fourth, these studies involved only a single judgment regarding each stock, whereas the real world is characterized by analysts reconsidering the same stock across multiple time periods. A stock considered “not a good buy” at one point in time might reflect “an excellent buy” at another point in time. Aside from providing greater correspondence with real-world security analyst decision making, multiperiod judgments are also necessary for assessing the concept of control schemata. Evidence for control schemata could reasonably be inferred only if individuals exhibited relatively consistent patterns across a set of comparable decision tasks. Computers can help with this problem by providing a convenient means through which large amounts of data can be efficiently collected and organized.

Fifth, these studies relied on drawing inferences from the post-decision results as to just which information weighed heavily in the decision making process. Using computer interactive assessment procedures would enable researchers to identify which specific information was actually being accessed as the decision process unfolded.

**Purpose of this Study**

The present investigation illustrates how computers can be used to overcome the limitations of prior research, thereby extending the range and usefulness of BP methods so as to permit the study of more complex processes and hypotheses. These advances are discussed in the context of a study that focuses on whether
Security analyst information

decision maker performance is related to differences in the extent and content of information accessing behavior.

METHOD

Sample

Subjects were recruited through invitations mailed to professional security analysts working for different investment banks in the Wall Street area. These letters indicated that research on security analyst decision making was being undertaken and would take the form of a competition with a $500 prize. More than twice as many analysts volunteered to participate than finally were able to participate. The high attrition rate was a result of several uncontrollable factors (e.g., an upsurge in market activity, scheduling problems, computer malfunctions). Notwithstanding these problems, the obtained sample was considerably larger than that employed by either Clarkson (1962), Slovic (1969) or Ebert and Kruse (1978), and is only one less than that employed by Slovic et al. (1972).

The final sample consisted of 3 females and 14 males. Seven were between 21 and 30 years old, seven were between 31 and 40, and three were over 40. Their careers as professional security analysts ranged from 1.5 to 17 years ($X = 6.9$ years, $SD = 5.7$), while the amount of time with their present employer ranged from 6 months to 6 years ($X = 2.3$ years, $SD = 1.8$). Fifteen had masters degrees (14 MBAs and 1 MS); two held BS degrees. Two analysts declined to respond to an item regarding the income they derived from their activities as professional security analysts. Another eight indicated that their income was below $75,000 a year; seven indicated that their income was above this amount.

Task and Instructions

Upon arriving at the test facility, analysts were asked to read the following description of the simulation and the rules for the competition.

The purpose of this task is to examine how professional security analysts make decisions as to which common stocks represent a good purchase.

In a short while, you will be asked to decide which one of eight stocks represents the “best buy.” (For the purposes of this study, the best buy is defined as that stock most likely to show the greatest percentage of growth in price per share over the next 90 day period.)

The eight stocks represent major U.S. retailing firms listed on the New York Stock Exchange during the years 1969–1970. . . . So that your knowledge regarding the present condition of these firms does not influence your decision making, we have given them fictitious names. However, all the information to which you will have access is authentic and is the actual information that was available for these stocks during the 1969–1970 period.

You will be able to acquire information on any of 26 different fundamental factors for each stock. A list of these factors is provided at the back page of these instructions. While we recognize that professional analysts often integrate yet other kinds of information into their decision making, for purposes of this task, you are asked to arrive at a decision based only on the 26 fundamental factors that are available.

Thus you will have access to 208 different items of information—that is, 26 items of information for each of 8 stocks (208 total items of information). All this information is stored in the computer. Since it would be unreasonable to expect you to keep all the
information in your head while you're arriving at your decision, a set of recording sheets has been provided so that, if you wish, you can make notes.

You will actually be making four different “best buy” decisions. The first will be for October 1969. Once you have made this decision, the computer will update the available information by three months (so that they reflect the data existing as of January 1970), and you will be asked to arrive at a second “best buy” decision regarding these same eight stocks. After you have reached this second decision, the information will again be updated by three months to reflect April 1970 data. This cycle is repeated for a total of four periods. In all, you will be asked to make four “best buy” decisions regarding the same set of 8 stocks, beginning with October 1969 and ending with July 1970.

Throughout, there are five basic rules you need to bear in mind as you go about obtaining information from the computer. These are:

1. You may obtain information only for the 3-month period provided. That is, you will not be able to go backward to access information from an earlier period, or forward to access information for a future date.

2. Within each period, you are free to examine up to 104 of the 208 items of information available. There is no “correct” or “right” amount of information to look at. You may choose to look at 2 items, 20 items or 100 items. It’s all up to you.

3. You may examine the available information in any order you want.

4. You may examine an item of information more than once. That is, you may return to look at information you have seen before. Simply instruct the computer to display that item again.

5. You are free to make as many or as few notes on the recording sheets as you like.

Although estimated that each session would require 1 1/2 to 2 1/2 hours, no time limit was imposed. The amount of time actually used ranged from 1 1/2 to 6 1/2 hours.

**The Information Environment**

For each test period, the available information environment consisted of 208 items of information—26 fundamental factors for each of eight companies. The factors were selected after both a review of the literature and consultation with knowledgeable colleagues revealed that this set was relatively comprehensive in covering the factors typically considered by security analysts. To eliminate the possibility of extraneous confounds, all stocks were drawn from the same industry. Thus, the variance attributable to market and industry-specific factors was held constant across the set of test securities. To reduce the possibility that the respondents’ memories would exert an effect upon information accessing, the data were taken from the period spanning October 1969 through July 1970. The only inauthentic information was the names of the companies: J, K, L, M, N, Q, R, S were used instead of the actual company names (Lane Bryant; Gimbels; Hughes and Hatcher; R. H. Macy; J. C. Penney; Sears Roebuck & Co.; F. W. Woolworth; and Zayres).

The fundamental factor information for each of these companies was taken from the *Monthly Stock Digest* published by Data Digests (1969-1970) and mailed monthly by Merrill Lynch to its clients. This was taken from the October 1969,
January 1970, April 1970, and July 1970 issues. Note that test periods 1, 2 and 4 reflected a relatively stable “bullish” market, whereas period 3 reflected a “bearish” market, that is, all eight stocks decreased in value during this period.

All information was stored in a Cromemco Z2H microcomputer. This represents a considerable advance over both the traditional research paradigm and antecedent BP (i.e., information display board) procedures, enabling the order of presentation of both the stocks and the fundamental factors to be instantaneously randomized across respondents (i.e., though each respondent worked with the same 8 stocks and 26 fundamental factors, these were presented in a different order for each respondent). This eliminates the problem of order effects sometimes observed when employing information display boards (e.g., Bettman & Kakkar, 1977). To avoid confusing the respondents, the random order generated for a respondent remained constant for that respondent across the four separate test periods. To further model the real world, once the random order had been determined for a given analyst, the computer printed out a blank security-by-fundamental factor matrix that the analyst could then use as a form of external memory.

Procedure

Testing took place during the summer and fall of 1982. Respondents commenced reaching their “best buy” decision for period 1 by communicating with the computer via a light pen attached to a color video monitor. After an initial series of interactions with the computer to review the task instructions and rules, two “menus” were displayed—one containing the names of eight stocks, and the other listing the 26 fundamental factors—and the analyst was asked to indicate which fundamental factor information he or she wanted to see for which security. Analysts were permitted to access only a single item of information at a time such as price-earnings ratio information for Company J. Accessing this information was accomplished by touching the screen twice with the light pen, once for each menu, and the desired information appeared on the screen almost instantaneously.

After acquiring this first item, the computer inquired whether the analyst wanted to make a “best buy” recommendation at that point or acquire additional information. If he or she replied that more information was desired, the two lists were displayed again and the light pen used to indicate which item the subject wished to consider. Each analyst continued in this way until he or she felt ready to make a “best buy” recommendation. This, too, was indicated via the light pen. After arriving at a “best buy” decision for period 1, the information for the eight securities was automatically and instantaneously updated by 3 months and the analyst proceeded in a similar manner to arrive at “best buy” decisions for periods 2, 3 and 4. None of the analysts evidenced any difficulty with this procedure.

Following all four periods, the analyst completed a brief questionnaire. In addition to collecting demographic and employment information, the subjects were asked whether they could identify any of the stocks used in the study. Only one analyst was able to do so and this was for only one firm. These data indicate that the identities of the stocks used for this study were successfully camouflaged.
Subjects were also asked if there were other types of information they would like to have had while they worked on picking “best buys.” Although 20 different factors were mentioned, thirteen of these were mentioned only once and only one (debt-to-equity ratio) was mentioned as often as three times. This suggests that the set of 26 fundamental factors was reasonably comprehensive in representing those fundamental factors generally considered by security analysts.

RESULTS

For the purposes of this study, the success of security analysts was based directly on the increases in price per share of each security, calculated separately for each of the four test periods. The analyst whose four choices produced the greatest net yield was declared the winner. The yields actually possible ranged from +33.1% to -76.3%. It is worthwhile noting that the analysts’ cumulative performance ranks across all four test periods were, in general, significantly related to their ranks across each of the four periods (period 1, \( r = .67, p < .002 \); period 2, \( r = -.10, p = .345 \); period 3, \( r = .78, p < .001 \); period 4, \( r = .50, p < .022 \)).

Several interesting findings emerge from a consideration of this “overall performance” index. First, had they invested money in a real world situation as they recommended in the task, only two of the analysts would have managed to make money: Seven would have lost 40% to 55% of the original value of their stocks. Much of this loss was experienced during period 3, which was characterized by a sharp market decline. In fairness to the participants, analysts operating in the real world are able to more closely monitor the day-to-day performance of their stocks and would not wait up to three months to divest themselves of a sinking security. If the performance index is based only on periods 1, 2 and 4, then the numbers are reversed, with 15 out of 17 analysts having positive indices (range = +35.4 to -7.2; \( \bar{X} = +14.25 \)). Also bear in mind that fundamental factor information accounts for only 30% to 35% of the factors believed to influence real world security analysis. Notwithstanding these qualifications, much real world evidence (cf. Business Week, 1985) suggests that our findings possess considerable external validity.

Second, performance was not related to several key characteristics. Across all 17 analysts, performance correlated nonsignificantly with age \( (r = -.22; p = .40) \), tenure with present employer \( (r = .37; p = .14) \), tenure as an analyst \( (r = .03; p = .92) \) and income \( (r = .04; p = .89) \).

Depth of Search

A Pearson correlation was conducted between performance scores for the 17 analysts and the number of items each acquired across all four test periods. These data show a significant positive correlation: the greater the amount of information acquired, the better the performance \( (r = .41; p = .05) \). However, much of this result is due to the extensive accessing of the top performing analyst. When he is removed, the correlation for the remaining 16 analysts hovers near .2.

The greatest insight is forthcoming when the search statistics for the five best
Table 1. Depth of Search Data for the Five Best and Five Poorest Performing Analysts

<table>
<thead>
<tr>
<th>Information Accessed</th>
<th>Overall</th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 3</th>
<th>Period 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Best</td>
<td>Poorest</td>
<td>Best</td>
<td>Poorest</td>
<td>Best</td>
</tr>
<tr>
<td>No. of different securities considered</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>7.8</td>
<td>8.0</td>
<td>7.2</td>
<td>8.0</td>
<td>8.0</td>
</tr>
<tr>
<td>Median</td>
<td>8.0</td>
<td>8.0</td>
<td>8.0</td>
<td>8.0</td>
<td>8.0</td>
</tr>
<tr>
<td>No. of different factors considered</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>8.7</td>
<td>9.0</td>
<td>8.8</td>
<td>13.6</td>
<td>8.4</td>
</tr>
<tr>
<td>Median</td>
<td>9.0</td>
<td>7.0</td>
<td>10.0</td>
<td>11.5</td>
<td>7.0</td>
</tr>
<tr>
<td>Percent of 208 item (stocks × factors)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>matrix accessed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>25.1</td>
<td>19.2</td>
<td>25.2</td>
<td>28.8</td>
<td>24.3</td>
</tr>
<tr>
<td>Median</td>
<td>25.0</td>
<td>14.4</td>
<td>28.6</td>
<td>22.3</td>
<td>16.6</td>
</tr>
<tr>
<td>Percent of submatrix accessed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>77.0</td>
<td>55.5</td>
<td>82.7</td>
<td>55.1</td>
<td>75.2</td>
</tr>
<tr>
<td>Median</td>
<td>72.0</td>
<td>53.5</td>
<td>74.0</td>
<td>50.5</td>
<td>61.6</td>
</tr>
</tbody>
</table>
the poorer performing analysts seemed to engage in a “fishing expedition” during the first period and then settled down to considering a substantially reduced set of factors in the second and subsequent periods.

One possible explanation for the difference between the two groups is that the poorer performing analysts based many decisions primarily on the information they acquired during the first period. This reflects the assumption of market insensitivity to short-term effects on stocks. In contrast, the top five analysts acquired the most updated information available in each period before arriving at their decisions. This latter group was more sensitive to possible short term market changes. Their tendency to update information counteracted the downward trend in amount of information acquired over the four periods that might have been predicted given their increasing familiarity with each stock.

Finally, an interesting perspective on the analyst's control schemata can be obtained by examining the “percent of submatrix accessed” variable, as reported in Table 1. While the 26 (factors) × 8 (stocks) information matrix made available to each subject contained all of the data for each security, not every piece of this information may have been useful, worthwhile, or even meaningful to all of the subjects. Hence, it is also insightful to adopt a respondent-oriented perspective and ask: If attention were limited to only those stocks and factors considered by the analyst at least once, then what percent of the information from that submatrix was accessed? The results of this study indicate that better performing analysts were consistently more thorough in examining the contents of their submatrices (77% overall) than were poorer performing analysts in examining the contents of their submatrices (55.5% overall).

Content of Search

Figure 1 provides a graphic representation of the accessing devoted to each fundamental factor by the five best and five worst performing analysts. Several findings are noteworthy.

First, for both the better and poorer performing analysts, four factors accounted for nearly 50% of the total search. These were last earnings trend, price-earnings ratio for the last 12 months, price last month, and adjusted annual earnings price per common share for the past 4 years—which together accounted for 42% of all the accessing done by the better performing analysts. For the poorer performing analysts, price-earnings ratio for the last 12 months, percent price change for the last 3 months, interim earnings for the last reported price per common share, and interim earnings for the previous year accounted for 48% of all their accessing. The only common factor across the groups was price-earnings ratio.

Second, to test for the presence of content-oriented control schemas, a chi-square test for the significance of the difference between independent proportions (Ferguson, 1966) was applied with the alpha level being set at .01 because of the multiple comparisons that were made. The proportion of accessing devoted to each factor was found to be significantly different between the two groups for 16 of the 26 factors (see Figure 1). (A less stringent test based on raw frequencies rather than proportions yielded significant differences for 19 of the 26 factors.) Thus, not only do good and poor performing analysts examine different amounts of information, but they also tend to consider different types of information.
Security analyst information

5 Best performing analysts

5 Worst performing analysts

1. P/E RATIO FOR LAST 12 MOS. = Ratio of Price to Latest 12 Months of Earnings
2. % PR. CHG LAST 3 MOS. = Percent Price Change—Last 3 Months
3. PRICE LAST MONTH = Price Last Month
4. LAST EARN. TREND (UP, DOWN, NO CHANGE) = Latest Earnings Trend (Up, Down, No Change)
5. EARN./COM. SHR-12 MOS. LAST QTR. = Earnings—Dollar per Common Share at 12 Months Ending the Latest Reported Quarter
6. ADJ'TD ANNL EARN. $/COM. SHR., PAST 4 YRS. = Annual Earnings—Dollar per Common Share (Adjusted for All Stock Dividends and Splits) for the Past 4 Fiscal Years
7. INT'M EARN. LAST REP'TD $/COM. SHR. RECENT REPORT = Interim Earnings—Latest Reported Dollar per Common Share at Most Recent Period
8. INT'M EARN. PREV. YR. $/COM. SHR = Interim Earnings—Dollar per Common Share for Previous Year
9. YLD ON INDICT'TD 12 MOS. OF DIV. = Yield on Indicated 12 Months of Dividends
10. EARN./COM. SHR.-12 MOS. ENDING NEXT-TO-LAST QTR. = Earnings—Dollar per Common Share at 12 Months Ending the Next Preceding Quarter
11. % NET PR. CHG. (LAST 9 MOS.) = Percent Net Price Change for Latest 9 Months
12. PR. RANGE CURRT. YR. HI-LO = Price Range for the Current Year—Hi/Lo (Prices Stated in Dollars)
13. LONG TERM DEBT = Long Term Debt
14. TOTAL CURRENT ASSETS = Total Current Assets
15. TOTAL CURRENT LIABILITIES = Total Current Liabilities
16. PR. RANGE LAST 10 YRS. HI-LO = Price Range for the Last 10 Years—Hi/Lo (Prices Stated in Dollars)
17. LAST DIV. TRND. (UP, DOWN, NO CHANGE) = Latest Dividend Trend (Up, Down, No Change)
18. CASH AND EQUIVALENTS = Cash and Equivalents
19. DIV.-($) PER COM. SHR., LAST YR. ANN'L RATE) = Dividends—Dollars per Common Share—Latest Interim Dividend
20. NO. OF COMMON SHARES = Number of Common Shares
21. NO. OF INST. HOLDINGS = Number of Institutional Holdings
22. NO. OF SHRS. HELD BY INST. = Number of Shares Held by Institution
23. CASH DIV./COM. SHR. LAST YR. ANN'L RATE = Cash Dividends per Common Share at Latest 12 Months or Indicated Annual Rate
24. NO OF PREFERRED SHARES = Number of Preferred Shares
25. CASH DIV./COM. SHR. THIS AND LAST CLNDR YRS. = Cash Dividends per Common Share at This and Last Calendar Year
26. DATE OF EX-DIV. = Date of Ex-Dividend: Listed as Month/Day

Figure 1. Comparing the profiles of accessed factors for the better versus the poorer performing analysts.
Third, the striking differences mostly occurred in regard to the four most heavily accessed factors. While both better and poorer performing analysts accessed price-earnings ratio information, the poorer performing analysts devoted a much greater proportion of their search to doing so. The difference becomes even more significant ($\chi^2 = 48.2, p = .001$) if one disregards the first period (based on the argument that it is an atypical session during which subjects got acquainted with the task) and compares the two groups only on periods 2, 3, and 4 (roughly 10% each period for the better analysts versus roughly 20% for the poorer analysts over the same time periods).

In similar fashion, poorer performing analysts devoted much greater attention to securing feedback (percent price change over the last 3 months) than did better performing analysts. This difference is also accentuated if one considers only periods 2, 3, and 4—the only periods for which this feedback is relevant. Across the last three periods, the better performing analysts devoted only 6% of their accessing to this factor while the poorer performing analysts did so nearly three times as often, or 17% of the time ($\chi^2 = 37.3, p = .001$). (An extended discussion of the findings regarding feedback is provided in Jacoby, Mazursky, Troutman, & Kuss, 1964.) In contrast, the top performing analysts begin devoting greater attention to the last earning trend factor (going from 11% in period 1 to an average of 15% during periods 2, 3, and 4, and ranked first overall in terms of which factors were accessed), while the poorer performing analysts begin devoting less attention to this factor (going from 6% in the first period to 3% in the second, third, and fourth periods, with an overall ranking of tenth) ($\chi^2 = 60.8, p = .001$).

If better performing analysts are distinguishable from poorer performing analysts in terms of the information they consider, does this mean that they rely on a common set of factors for decisions making? To answer this question, the information accessed by these analysts during the final period was examined. In all, these five analysts considered 20 different factors. Eight factors were considered by only a single analyst; another eight were considered by just two of these analysts. The data for the remaining factors are as follows: (a) last earnings trend—five analysts, (b) price last month—five analysts, (c) price-earnings ratio for the last 12 months—four analysts, and (d) earnings per common share for the 12 months ending last quarter—three analysts. Given the low degree of commonality, these data suggest that different content control schemata may prove equally effective, at least in the short run.

**DISCUSSION**

After reviewing the principal findings, their limitations and implications, attention is directed toward application and extension of the computer-assisted research paradigm described herein. Throughout, it is important to emphasize that the focus is not on analyst performance per se, but on the information accessing strategies (viz. depth and content of search) that were employed and seemed to contribute to better or poorer performance. Note also that this research would be virtually impossible to conduct without the storage, display, and recording capabilities of computers.
Principal Findings

By focusing on the information that goes into security analyst “buy” decisions, this investigation found dramatic differences in the information accessing strategies employed. As compared to poorer performing analysts, better performing security analysts not only acquired more information, but also tended to examine different types of information. These findings are interpreted as providing support for the concept of content and quantity driven control schemas (Kozminsky et al., 1981).

At least two explanations may account for the relationship between amount of information acquired and performance. First, handling more information directly leads to better decision making. Consistent with the control schema notion, an alternative explanation is that systematic information acquisition first leads to an ability to handle greater amounts of information and this leads to better decision making. The data (specifically, a consideration of the percent of submatrix statistics for the two groups) seems to support this second explanation. This leads to a fundamental question: Just what is it that distinguishes between systematic and nonsystematic information accessing? Work is currently being conducted to address this question.

Limitations

Like any investigation, this study is not without limitations. Most obvious is the fact that the sample was limited to 17 volunteer analysts and that the bulk of data analyses were performed using only 10 of these individuals (the five best and five worst performers). Greater confidence would be obtained from a larger and more representative sample.

Second, by focusing only on fundamental factors, the study addresses only 30% to 35% of the variance estimated to occur in security analyst decision making. One can only speculate as to what might have occurred had the other 65% to 70% of the variance been adequately modeled and included. Notwithstanding this limitation, it is hard to see how inclusion of these other elements would have exerted any great or interacting impact over the accessing of fundamental factor information.

Third, analysts were only permitted to make “buy” recommendations; there was no way for them to also provide “sell” recommendations. Perhaps they would not have performed so poorly, especially during period three, had they been able to make such sell recommendations. As Bernstein (1975, p. 60) points out, making buy recommendations represents only half the security analyst’s job. Equally important in security analyst decision making is a focus on the “prevention of serious error.”

Finally, the analysts were permitted to make only one recommendation per period. Yet, in the real world, analysts generally adopt a portfolio perspective, making buy and sell recommendations for more than a single security at a time. Research that corrects for these four limitations is now under way.

Implications

Both theoretical and applied implications exist. On a theoretical level, the data suggest that better performing decision makers do employ different content and
depth oriented “control schemata” to guide their pre-decision information accessing and analysis, although the precise nature of these schemata, at least in terms of content, may differ from one expert to another.

On a somewhat more applied level, the present findings suggest an answer to the question: What factors, if any, differentiate between good and poor security analyst decision making? The “if any” caveat is not idle. Controversy exists over whether the “don’t buy, buy, hold, sell” recommendations issued by professional security analysts represent a valued source of information for the individual investor. Some contend that such research has potential value (Bernstein, 1975; Black, 1973; Clarkson, 1962; Graham et al., 1966; Lloyd-Davies & Canes, 1978; Ruff, 1963; Stanley, Lewellen, & Schlarbaum, 1981); others argue such research possesses little or no value (Bidwell, 1977; Colker, 1963; Cowies, 1933, 1944; Cragg & Malkiel, 1968; Diefenbach, 1972; Ferber, 1958; Logue & Tuttle, 1973; McCain & Miller, 1975; Shepard, 1977; Stoffels, 1966). This latter camp reflects what has come to be known as the efficient market hypothesis. According to Lorie and Hamilton (1973); “The most general implication of the efficient market hypothesis is that most security analysis is logically incomplete and valueless” (p. 100).

The issue is clearly an important one from at least two perspectives. For the individual investor, “such recommendations may be the paramount influence on their portfolio decisions and, therefore, a major determinant of the effectiveness with which they can participate in an equities market that has increasingly come to be dominated by institutional traders” (Stanley et al., 1981, p. 1). From the perspective of the brokerage house, analyst recommendations may be an important factor in the investor’s decision to patronize one brokerage firm rather than another. As a result, “competition among brokerage houses for commission revenue business often centers on the proclaimed quality of the various firms’ respective research outputs” (Stanley et al., 1981, p. 1). Regardless of which perspective one adopts, it is clear that “individual investors are paying for large quantities of this research, either directly through subscriptions to investment advisory services or indirectly in the commissions charged by brokerage firms that supply securities recommendations to their customers” (Stanley et al., 1981, p. 1).

Prior research tended to treat security analyst recommendations in rather simplistic, all-or-none fashion, as if all such decisions either did or did not possess value. Instead, the present study directed attention to the question, “Just which factors differentiate between recommendations that possess value and those which do not?”

The data also shed light on another important question, namely: To what kind of fundamental factor information do better performing analysts devote most of their attention? Just 4 of the 26 factors account for 42% of all the information accessed by the better performing analysts. Is this information the same or different from that most often accessed by the poorer performing analysts? The answer is that except for price-earnings ratio, the poorer performing analysts devote a negligible proportion of their accessing to the three other fundamental factors.

Some may ask why this investigation found substantial differences between the better and poorer security analysts while many others report finding no such
difference. At least two answers apply. First, this investigation was confined to fundamental factor information which supposedly accounts for only 30% to 35% of the variance in real world security analysis. Conceivably, the inclusion of information representing the remaining 65% to 70% could introduce offsetting effects such that the net outcome would reflect no meaningful performance differences across analysts. Although plausible, this explanation is counter-indicated by the fact that much of this additional variance is associated with market and industry-specific factors and these could be presumed to exert relatively constant effects across all stocks in a common industry.

A more viable explanation relates to the data collection method employed. BP methods, particularly when coupled with computer administration, enable one to examine information accessing behavior concurrent with the process itself and in terms of discrete and relatively molecular information accessing. In contrast, most other research has relied on post-decision recall of information accessing behavior. Considerable evidence now exists to show that verbal reports regarding such dynamic mental processes tend to be highly fallible (cf. Nisbett & Wilson, 1977).

The present study also has practical implications for the selection and training of security analysts, or, for that matter, the selection and training of any type of decision maker operating in contexts for which there exist accepted objective criteria for identifying good decision making (e.g., medical diagnosis, retail buyer decision making). Nobel prize winner Penzias (1982) comments: “Before we can even try to design an expert system, we must discover what it is that experts do” (p. 28). The present research moves in the direction of such expert modelling. Given that further research (especially that which accommodates for the limitations noted above) replicates our findings, we can begin to suggest just which fundamental factors should be considered by security analysts when arriving at “buy” decisions. The next step would be to develop simulations for use in both selection and training such as for diagnosing and modifying the information accessing control schemata of practicing analysts and evaluating the potential of prospective security analysts. Work is currently proceeding along these avenues.

**Computer Oriented Applications and Extensions**

Some of the ways in which computer assisted BP simulations can be used to rectify numerous problems associated with traditional verbal report and information display board paradigms have already been illustrated, including the ability to handle large data arrays and display selected portions of these on demand; rapidly update the contents of these arrays so as to facilitate multi-period and multi-decision research; and provide information in randomized orders across different subjects. This concluding section touches on other adaptations and extensions generally only possible with the computer, the cumulative effect of which is to enhance internal validity, external validity, and generalizability.

The present investigation utilized a two-dimensional option × property (i.e., security × fundamental factor) information environment. Yet the external information environment can be conceptualized as having three major dimensions: options × properties × sources. The present investigation held source constant;
all information came from one source, the *Monthly Stock Digest*. Yet the source dimension is relevant for many decision and judgment tasks, for example, in reaching a decision as to which contraceptive to use, the consumer may consult a physician, friends, spouse, magazine article, and so forth. While two-dimensional arrays can be handled by information boards, computers are about the only reasonable way to study three-dimensional arrays (cf. Chestnut & Jacoby, 1980; Hoyer & Jacoby, 1983).

Often, the amount of time the decision maker spends considering a particular item or type of information is of theoretical importance (cf. Jacoby, Szybilko, & Berning, 1976). Such assessments are generally made using stop watches and recorded by hand (Rudd & Kohout, 1983). Computer-assisted research can eliminate this error-prone assessment procedure. Relatedly, there may be times when, for purposes of better simulating the real world, it would be useful to incorporate a constant or variable time delay between the point in time at which information is requested and the point at which it is displayed. Computer-assisted paradigms facilitate such research.

At a very basic level, computer-assisted simulations also more readily lend themselves to manipulation, thereby enabling one to conduct true experiments and enhance validity. As an applied example, consider the manufacturer trying to decide which of three names to use for a new toothpaste. Using a computer assisted BP paradigm and a between-subject design, a researcher could pit each of these three names against a standard set of other options to determine the impact of each proposed name on depth, content and sequence of information acquisition and on subsequent choice behavior. The contents of specific cells in the array (e.g., the price for brand X) could also be systematically manipulated in this manner and the impact of this manipulation on the same dependent measures assessed. Relatedly, and as illustrated in Jacoby, Mazursky, Troutman, and Kuss (1984), computer-assisted BP research permits one to study various aspects of feedback (e.g., active versus passive accessing) which have heretofore generally gone unrecognized and do not readily admit to being studied by any other means.

Increasingly, computer-assisted simulations are enhancing the validity of decision making research because real world information accessing is being carried out more and more often with the aid of computers. The computer itself has evolved from a tool used by researchers to a significant part of the daily environment for many professionals. Nowhere is this more true than in the world of security analysts, who derive much of their daily information from computers. Thus, using a computer driven methodology is an excellent means by which to emulate very closely the real world decision making experiences of these and other professionals. On a related point, increasing usage of on-line data bases in everyday work activity raises the real possibility of conducting decision making research using “live” data and measuring outcomes as they occur naturally.

While the study described in this report was conducted with several relatively large pieces of hardware, none of which were designed for portability, our most recent ongoing investigations are being conducted on standard microcomputers. It is no longer necessary to construct and transport cumbersome information display boards. By reproducing our disks and/or utilizing modems, we will be able to conduct the same study at many different places at the same time and reduce
subject attrition by eliminating many problems associated with travel and scheduling. This will substantially increase the number of subjects available to BP researchers and thus help to improve the validity of research in this area, in addition to decreasing costs and increasing the speed of BP research.

To this point, computer-assisted BP research has been limited to studying information conveyed in alpha-numeric form. Any use of graphic or pictorial stimuli has necessitated unwieldy manual presentation formats (cf. Mazursky & Jacoby, 1985). However, computer-controlled video disk technology (cf. Hooper, 1981) would permit the easy integration of both static (e.g., newspaper ads) and dynamic (e.g., TV) video stimuli into BP research. Computers could also be mated with audio (e.g., radio) input to further broaden the range of BP applicability.

One final extension is noted here. To this point, the focus of BP research has been on studying the information accessing process per se (specifically, the quantity, content and sequence of such accessing), and the relationship of this process to judgment or decision outcome (cf. Jacoby, Chestnut, Hoyer, Sheluga, & Donahue, 1978). Yet judgment and decision making are generally conceptualized as dynamic processes wherein information accessing represents but a preliminary stage antecedent to central processing, with the latter reflecting a great variety of interesting cognitive variables. Theoretically and pragmatically, important questions include, what is the effect of information accessing on beliefs, impressions, attitudes, intentions, etc.? Although completely unwieldy in any but the simplest of manual systems, computer-assisted BP simulations are amenable to having one or two scales inserted immediately after each item of information has been accessed, thereby permitting one to track the impact that the information just accessed exerted on the cognitive phenomenon of interest. For example, in an NSF-sponsored study of birth control decision making, after one item of information was accessed but before accessing another, subjects used a light pen to respond to a 100-point scale that posed the following question: "How certain are you at this point that you will be able to select the safest birth control method from among the 10 types available?" As compared to a no-tracking (i.e., standard BP) control group, such tracking generated no reactive effects on either the quantity or sequence of information accessed. (These findings were replicated with different subjects tested on household insecticides and automotive tires.) Yet while the control group only permits one to examine pre-versus post-task changes in uncertainty, the tracking condition permits one to trace the item-by-item impact on this key cognitive phenomenon (cf. Jacoby, Kuss, Troutman & Mazursky, 1985.) In contrast, when the senior author attempted to introduce such a tracking manipulation into an information display board context in 1976, he found the effort completely unwieldy.

Placing BP simulations into a computer-assisted format thus opens the door to studying the impact of information acquisition on a broad spectrum of phenomena conceptualized to operate as dynamic information response cognitive processes. Especially when coupled with the capability of studying pictorial stimuli afforded by introducing computer-controlled video disks, the opportunities for studying the responsiveness (qua development and change) of cognitive phenomena to self-selected information input that is provided by mating the BP paradigm to computers opens the door to years of fruitful programmatic research.
REFERENCES


