Taking Stock of Stockbrokers: Exploring Momentum versus Contrarian Investor Strategies and Profiles

MAUREEN MORRIN
JACOB JACOBY
GITA VENKATARAMANI JOHAR
XIN HE
ALFRED KUSS
DAVID MAZURSKY*

Two studies were conducted among professional security analysts to explore their patterns of decision making while managing investment portfolios. In study 1, a computer-based simulation, the analysts' styles differed markedly, with most exhibiting either a momentum or contrarian approach, as indicated by responses to portfolio stock price changes. Study 2 used a verbal protocol procedure and semistructured depth interviews to probe the analysts' thought processes. Momentum and contrarian investors were found to differ on a number of dimensions including price expectations, age, experience, raw performance, risk propensity, cognitive style, knowledge calibration, and strategy adaptivity. Implications and limitations are discussed.

Despite its prominent role in contemporary society, surprisingly little is known about the information-processing and decision-making strategies of professional stock market investors. A strict interpretation of traditional finance theory, with its focus on aggregate marketplace behavior, would suggest that investors are rational mean-variance optimizers operating in an efficient market where stock prices reflect their true values (Bodie, Kane, and Marcus 1999). The nascent field of behavioral finance theory has challenged several of the assumptions of the traditional paradigm. Theorists such as Shiller (1993), De Bondt and Thaler (1985), and Shefrin and Statman (1993) have attempted to provide psychological explanations for the emerging empirical evidence of marketplace anomalies at odds with efficient-market theory. Our research explores which, if either, of these approaches is exhibited by the cognitive processing and investment decision-making of professional security analysts who take part in two stock-picking simulations.

The behavioral finance framework suggests that the collective impact of individual decision makers' psychological biases may cause stock prices to be temporarily over- or underpriced relative to their true economic value (e.g., Shiller 1993). In support of this view, it has been shown that investors often overreact, for example, by excessively bidding down a stock price after learning of negative firm news. Graham and Dodd (1934), recognizing this possibility, were some of the earliest proponents of a contrarian approach to investment. They suggested that, because the market as a whole tends to overreact to negative news, some firms' stocks temporarily become undervalued and thus represent buying opportunities. De Bondt and Thaler (1985) carried this notion further by suggesting not only that in-

*Maureen Morrin is assistant professor at the University of Pittsburgh, Katz Graduate School of Business, Mervis Hall, Pittsburgh, PA 15260 (mmorrin+@pitt.edu). Jacob Jacoby is Merchants Council Professor at New York University, Stern School of Business 8-97, 44 West 4th St., New York, NY 10012 (JJacoby@Stern.NYU.edu). Gita Venkataramani Johar is associate professor at Columbia University Business School, 519 Uris Hall, New York, NY 10027 (gvj1@columbia.edu). Xin He is a doctoral student at the University of Pittsburgh, Katz Graduate School of Business, Mervis Hall, Pittsburgh, PA 15260 (xinhe@pitt.edu). Alfred Kuss is professor at Freie Universitat Berlin, Institut fur Marketing, Garystrasse 21, 14195, Berlin, Germany (ls-kuss@wiwiss.fu-berlin.de). David Mazursky is professor at Hebrew University, Jerusalem School of Business Administration, Jerusalem, Israel 91905, and at Bocconi University, Milan, Italy (msmazur@mscc.huji.ac.il). The authors thank Merrie Brucks, Martin Gruber, Rajiv Kohli, Richard Olshavsky, the reviewers, the associate editor, and especially the editor for helpful comments. They also thank RongRong Zhou for help in data collection. This research was funded in part by the University Research Council of the University of Pittsburgh and in part by the New York University Stern School of Business.

vestors overreact to negative news but also that they overreact to positive news, resulting in overpriced stocks. Because of these tendencies, contrarian investors often expect that stocks that have fallen in value will rebound and that stocks that have risen in value will fall. Thus a typical contrarian investor buys out-of-favor stocks and sells popular stocks. Some studies have found support for contrarian approaches to investment under certain market conditions (e.g., Basu 1977).

Another marketplace anomaly that may reflect the impact of individual investor psychology is the observation of positive serial correlations in stock prices, also known as the "momentum effect" (e.g., Jegadeesh and Titman 1993). The phenomenon has been explained from a social psychological perspective, where a herdlike mentality influences stock valuations beyond those supported by economic fundamental factors (Shefrin and Statman 1993; Shiller 1993). The existence of positive serial correlations implies that if a stock price has recently risen (fallen), it is more likely to rise (fall) than fall (rise) in the next period. Momentum investors thus typically buy growth stocks, those whose prices have been rising due to prevailing market beliefs, while selling off losers, those whose prices have been falling.

Do professional security analysts tend to exhibit either of these or other behavioral tendencies when choosing to buy, sell, or hold stocks in investment portfolios? Can we accurately infer an analyst's underlying decision-making strategy from his or her pattern of behavioral responses to stock price changes over time? If individual analysts exhibit clearly identifiable styles of decision making based on their reaction to stock price changes, are there other characteristics, such as age, experience, thought processes, performance, or risk propensities that differentiate these investor groups? Do analysts ever believe they can beat the market, and how accurate are their self-assessments? Do they remain committed to their decision-making strategies even in the face of lackluster performance, or do they adapt their strategies over time? These and related issues are explored in the following two studies.

STUDY 1

Subjects

The subjects were 19 practicing security analysts (14 males, five females) working for investment firms in the New York metropolitan area. They were recruited via an announcement for a stock-picking competition that appeared in the newsletter of the New York Society of Security Analysts. There were two incentives for participation: money for first ($500) and second ($100) place winners and publicity for the top 10 finishers via a press release sent to relevant local media. The subjects' mean age was 32.1 years (range: 24–54), with an average of 9.1 years experience as an analyst.

Test Stimuli

Securities listed on the New York Stock Exchange and drawn from the pharmaceutical industry during the 1983–1984 time period were chosen for the study because this period provided fairly stable to slightly increasing values for pharmaceutical securities listed on the New York Stock Exchange. Turbulent stock market periods (e.g., the crash of 1987) and volatile industries (e.g., retailing in the late 1980s) were avoided. The six securities selected were chosen so as to ensure a variety of firm sizes and price trends (table 1).

The Information Environment

Analysts had access to 23 types of fundamental factor information, information related to a company's financial statements (exhibit 1), for each of the six securities. Selection of these 23 factors from over 300 in the Compustat database was based on previous research (Ou and Penman 1989) as well as on ratings obtained from three faculty members and a doctoral student in the finance department at one of the universities where this research was conducted. To stimulate variability and differentiation, the 23 factors were selected so that 20 were among those consistently rated most important and three were consistently rated as unimportant. To preclude the impact of preexisting knowledge, a randomly assigned letter was used to identify each security.

The Decision Task

The procedures of study 1 were designed by Jacob Jacoby to be advances over those used in earlier investigations in this area (Jacoby et al. 1985, 1987). Using a laptop computer, we conducted the experiment on an individual basis, usually in the analyst's office. Analysts read instructions informing them that their task was to maximize the value of an initial $1,000,000 stake through investment decisions they would be making over four consecutive 90-day time periods. These instructions informed the analysts that they had seven investment options—the six pharmaceutical stocks and an interest-bearing cash account (earning 2% per quarter, compounded quarterly). Their task was

TABLE 1

STUDIES 1 AND 2: PRICE CHANGE OF STOCK FROM PREVIOUS QUARTER

	Quarter			
Stock	1 (% change)	2 (% change)	3 (% change)	4 (% change)
1	34.0	52.3	33.3	5.8
2	−21.0	−18.1	−11.6	5.3
3	32.2	3.1	−10.0	−8.3
4	−16.1	−7.4	11.1	−1.4
5	.0	−10.8	19.5	20.4
6	−6.3	4.2	−1.7	−10.7

EXHIBIT 1

FUNDAMENTAL FACTOR INFORMATION AVAILABLE FOR EACH STOCK

Fundamental factors
1. Assets (Total)/Liabilities
2. Capital Expenditures
3. Cash and Cash Equivalents: Increase (Decrease)
4. Common Equity (Total) (Annual)
5. Current Assets
6. Current Liabilities (Total)
7. Debt: Capitalized Lease Obligations (Annual)
8. Depreciation and Amortization
9. Dividends per Share
10. Earnings per Share
11. Income Available for Common Stock Equivalents
12. Interest Capitalized: Net Income Effect
13. Inventories (Total)
14. Long-Term Debt (Total)
15. Net Income (Loss) and Pretax Income
16. Prepaid Expenses (Annual)
17. Percentage Price Change in Quarter
18. Price: High, Low, and Close of Quarter
19. Receivables (Total)
20. S&P Bond Rating (Annual)
21. Sales (Net)
22. Short-Term Investments
23. Working Capital Change

to create a portfolio for each period consisting of any combination of the investments. They were informed that the winner would be the person who managed to increase the cumulative return on their investment holdings by the greatest amount by the end of the fourth period.

To help the analysts with their task, we also told them that before deciding on their portfolio for each period they could access all, some, or none of 23 types of fundamental factor information available for each of the six securities. The fundamental factors and securities were presented as two menu lists, with the entries on these lists randomized across subjects. After a decision had been reached for a period, the computer automatically updated this information. Though permitted to record any information acquired, subjects were told they would be able to access information only for the quarter they were in. Before taking part in the stock-picking simulation, the analysts completed a practice task in an unrelated choice domain to familiarize them with how the computer program worked.

Results

Information Processing. Although able to access a total of 552 (23 × 6 × 4) items of information during the four periods, the analysts were quite selective, accessing a mean of 120 items of information over the course of the simulation. Accessing activity trailed off considerably after the first period (period means: $M_1 = 57$, $M_2 = 21$, $M_3 = 19$, $M_4 = 17$; M_1 was greater than each of the other means at $p < .0001$). The analysts took an average of 32.4 minutes to complete the investment task. There were significant differences in the frequency of accessing by information type ($\chi^2(21) = 1{,}749$, $p < .001$), with earnings, sales, price: high/low/close, and percentage price change the most frequently accessed items. The least-accessed items were prepaid expenses, interest capitalized, and short-term investments, namely, the three types of information consistently rated unimportant before the study.

Performance. Each analyst's performance was determined by the change in value of the $1,000,000 opening stake from the beginning to the end of the simulation. For the given data set, the best- and worst-ending balances possible were $3,275,377 (+228%) and $510,757 (−48.9%). The best and worst performances obtained were about half of those possible, namely, $2,163,000 (+116%) and $798,000 (−20.2%), respectively, with a mean performance of +23.3%. There was high intraindividual reliability, with the performance of each analyst remaining fairly consistent from one period to the next. The correlation between individual analyst performances in periods 1 and 2 was $r = .71$; between periods 2 and 3 it was $r = .68$; and between periods 3 and 4 it was $r = .69$ (all significant at $p < .01$). (Performance is measured as percentage change in portfolio value from one period to the next.)

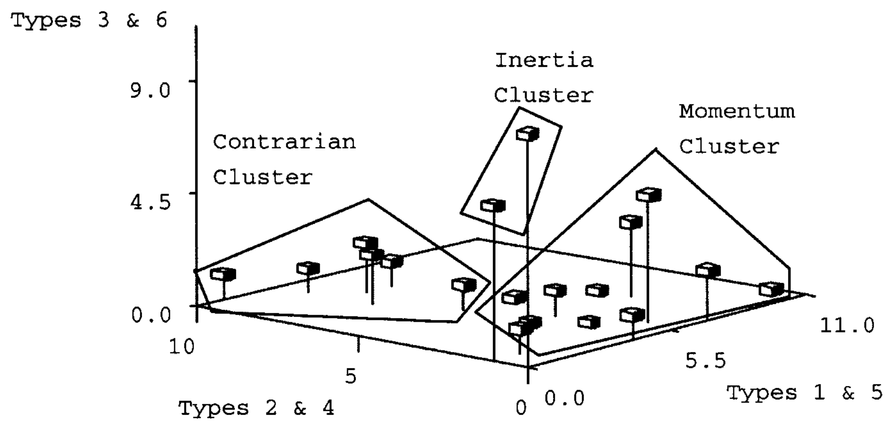
Reaction to Price Changes of Stocks in the Marketplace. The analysts' reactions to stock price changes over time were examined in terms of how they altered their portfolios after learning that stocks in the market had risen or fallen in value. There were a total of 323 observations (19 analysts × 17 stock price changes) for analysis. The analysts were about equally likely to act (by buying or selling) as to stand pat (i.e., make no change to their holdings) after learning about a stock price movement (46.4% vs. 53.6%, $\chi^2(1) = 1.17$). Moreover, given that an analyst decided to act in response to a price change, he or she was about equally likely to buy as to sell the stock (26.9% vs. 25.4%, $\chi^2(1) = 0.14$).

Reaction to Price Changes of Stocks in Their Own Portfolios. We next examined how the analysts responded to price changes of stocks held in their own portfolios. We expected these price changes might be more salient to analysts, since they have a direct and immediate impact on individual performance. There were 227 observations for analysis. (Allocation decisions in period 1 were excluded because portfolios had not yet been constructed.) The analysts were about twice as likely to act (i.e., by buying or selling) as to stand pat (i.e., make no changes to holdings) after learning about a price change of a stock in their own portfolio (68.7% vs. 31.3%, $\chi^2(1) = 31.83$, $p < .001$).

To examine this finding in more detail, we coded the types of responses analysts made after learning that a stock in their portfolio had changed in value. For example, after learning that the price of a stock in their portfolio had risen in value, an analyst could decide to buy more of that stock (a momentum type of response, coded type 1), sell some or all of that stock (a contrarian type of response, coded type

FIGURE 1

ANALYSTS CLUSTERED BY RESPONSES TO PRICE CHANGES OF STOCKS HELD IN THEIR PORTFOLIOS



2), or make no changes to their holdings of that stock (an inertia type of response, coded type 3). After learning that the price of a stock in their investment portfolio had fallen in value, an analyst could buy more of the stock (a contrarian type of response, coded type 4), sell some or all of the stock (a momentum type of response, coded type 5), or make no changes to their holdings of the stock (an inertia type of response, coded type 6).

We first examined the analysts' response patterns in the aggregate and observed about equal propensities for momentum (types 1 and 5: 37.4% of total), contrarian (types 2 and 4: 31.3% of total), and inertia responses (types 3 and 6: 31.3% of total; $\chi^2(2) = 1.726$). Thus, at the aggregate level, patterns in response to decision feedback were not evident. However, we speculated that the aggregate level analysis might be masking significant individual differences in patterns of response. We therefore conducted a cluster analysis of the analysts as a function of the number of each of the six possible types of decision feedback responses they made.

Cluster Analysis. Based on the two-stage algorithm suggested by Punj and Stewart (1983), we used an agglomerative hierarchical technique (Ward's method) to arrive at a preliminary solution regarding cluster number. At this stage, three clusters that explained 65% of the variance emerged. Subsequent clusters exhibited significantly less explanatory power, with semipartial R-squares of less than 10% each. A visual inspection of the resulting dendogram confirmed the existence of three fairly well separated clusters. A three-cluster solution was thus deemed appropriate for segmenting the analysts. We then conducted a k-means partitioning of the data to arrive at a final three-cluster solution (Punj and Stewart 1983). The three clusters contained $n = 11$, $n = 6$, and $n = 2$ analysts each.

The largest cluster ($n = 11$) exhibited a predominant tendency to buy winners (type 1 response) and sell losers (type 5 response; see fig. 1) from their portfolios. That is, they tended to buy more of a stock they owned that had recently risen in value and to divest themselves of stocks that had recently fallen in value. We labeled this cluster the "momentum investors." The second largest cluster ($n = 6$) exhibited the opposite pattern of behavior. Specifically, they tended to buy low (type 4 response) and sell high (type 2 response), that is, to buy more of a stock they owned that had recently fallen in value and to sell some or all of a stock that had recently risen in value. We labeled this cluster the "contrarian investors." The third and smallest cluster ($n = 2$) exhibited neither of these behavioral tendencies. Instead, this group tended to exhibit inertia in the face of recent stock price changes (type 3 and 6 responses). Thus, they tended to make no changes to their portfolio allocations as a result of learning that the prices of stocks in their portfolio had risen or fallen in value. We labeled this cluster the "inertia investors"; however, due to its small size ($n = 2$), we refrain from discussing individual comparisons between this cluster and the others in the remainder of the analysis. Having established distinct investor clusters on the basis of response to decision feedback, we next examined whether the clusters differed on dimensions other than those used to conduct the cluster analysis.

Demographics. The investor clusters differed in age ($F(2, 14) = 4.59$, $p < .05$, $R^2 = .39$; two analysts declined to provide their ages), with contrarian investors ($M = 38.4$ years) older than momentum investors ($M = 29.2$ years, $p < .01$) by nearly a decade. The investor clusters also differed in mean years of experience as a security analyst ($F(2, 15) = 5.59$, $p < .05$, $R^2 = .43$; one analyst declined to provide this information), with contrarian investors ($M = 15.5$ years) significantly more experienced in the decision-making domain than momentum investors

($M = 5.0$ years, $p < .005$). Similarly, the investor clusters differed in experience evaluating stocks in the pharmaceutical industry ($F(2, 15) = 3.86$, $p < .05$, $R^2 = .34$), with a higher proportion of the contrarian investors (83.3%) than the momentum investors (30.0%, $p < .05$) having had this type of experience.

Information Processing. A mixed-model analysis was conducted on the mean time taken to examine each item of information accessed as a function of investor cluster, simulation period, and their interaction. Investor cluster was significant ($F(2, 16) = 5.58$, $p < .05$), indicating that the contrarian investors spent significantly more time examining accessed items of information than did the momentum investors ($M = 24.7$ vs. $M = 10.8$ seconds, respectively, $p < .005$). Neither simulation period ($F < 1$) nor the investor cluster by period interaction ($F(6, 48) = 1.55$, $p > .15$) was significant.

Performance. A mixed-model analysis was conducted on the raw returns of each analyst's stock portfolio as a function of investor cluster, simulation period, and their interaction. Investor cluster was significant ($F(2, 16) = 3.63$, $p < .05$), indicating that the momentum investors exhibited better per-period raw performance ($M = 9.9\%$) than did the contrarian investors ($M = 5.6\%$, $p < .05$). Simulation period was also significant ($F(3, 48) = 10.46$, $p < .0001$), but this result is an artifact of the data set, which exhibited higher possible returns in the middle two periods. The period by cluster interaction was not significant ($F(6, 48) = 1.34$, $p > .25$).

We also compared the clusters on risk-adjusted performance using Sharpe ratios (Sharpe 1964), a standard measure of risk-adjusted returns (Bodie et al. 1999). (The risk-free rate was considered the 2% cash account quarterly return.) A mixed-model analysis of risk-adjusted returns as a function of investor cluster, simulation period, and their interaction showed that investor cluster was no longer significant ($F(2, 16) = 1.70$, $p > .20$). This result indicates that once the analysts' returns are adjusted for the level of risk reflected in their investment portfolios, there are no longer significant performance differences among the investor clusters. Simulation period was significant ($F(3, 48) = 11.19$, $p < .0001$), indicating that mean returns were higher in the middle periods of the simulation (as before, an artifact of the data set). The period by cluster interaction was not significant ($F < 1$).

Discussion

Study 1 clearly demonstrates that analyst behavior is heterogeneous in nature. The analysts exhibited a wide range of raw performance levels (from −20.2% to +116.0%) resulting from the construction of individual investment portfolios. At the aggregate level of analysis, behavioral responses (i.e., buy, sell, hold) to price changes did not reveal any systematic patterns. However, when analyzed on the basis of responses to price changes of stocks held in their own portfolios, the analysts exhibited very clear patterns of behavior. Specifically, the analysts were found to be twice as likely to change their holdings of a stock (vs. stand pat) after learning that its price had changed. Thus, the analysts did not seem to interpret price changes of stocks in their portfolios as random walks. Instead, most seemed to interpret price changes of stocks they held as information cues regarding the future direction of stock prices; these perceived cues then influenced their subsequent investment decisions. To our knowledge, this is the first attempt to categorize investors on the basis of response to price changes of stocks held in investment portfolios as well as to find differentiating characteristics among individual analysts categorized on this basis.

A cluster analysis revealed that most (17 of 19) of the analysts exhibited one of two major patterns of response to price changes of stocks in their portfolios: momentum or contrarian. Momentum investors seemed to interpret price increases of stocks they held as signals to buy and price declines of stocks they held as signals to sell. Thus, they bought and sold stocks as if they expected prices to keep going in the direction they had already exhibited. Contrarian investors seemed to interpret portfolio stock price changes in the opposite manner. For these analysts, price increases of stocks they held seemed to be interpreted as signals to sell, and price decreases of stocks they held seemed to be interpreted as signals to buy. The contrarians thus bought and sold stocks as if they expected price reversals.

The momentum and contrarian investors differed not only in how they responded to price changes of stocks held in their portfolios but also in terms of their demographic characteristics, cognitive-processing styles, and raw performance and portfolio risk levels. The contrarians were about a decade older, significantly more experienced in investment analysis, and more likely to have had experience evaluating pharmaceutical stocks than the momentum investors. What might account for this intriguing finding? Is it that older investors become more risk averse as a function of the chronological aging process? Or is this result a function of work experience: Do more experienced investors eventually adopt a contrarian approach to investment because they are more likely to have personally experienced significant market downturns in the past and thus are more likely to expect market reversals? This is one issue we attempt to explore in study 2.

Compared to the momentum investors, the contrarians also spent more than twice as much time processing each item of information accessed. It seems likely this finding is a result of differences in the extent of systematic processing engaged in by the two types of investors. The exact nature of this difference is another issue explored in study 2.

The two groups also differed in overall raw performance, with the momentum investors significantly outpacing the contrarians. A comparison of risk-adjusted scores, however, revealed no significant differences. This set of results indicates that the momentum investors achieved their higher raw performances by building riskier portfolios, that is, more volatile stock combinations. It is not clear whether momentum investors recognize that they are taking on more risk when they construct their portfolios or whether the contrarians deliberately try to avoid constructing highly volatile stock portfolios. Study 2 was designed to provide insight into this issue as well.

STUDY 2

To gain additional insight into the thought processes underlying investment decisions made by professional security analysts, we conducted a decision-making simulation among nine other analysts using a verbal protocol procedure (e.g., Ericsson and Simon 1993) followed by semistructured depth interviews. Although the computer-based method used in study 1 was effective at precisely measuring information acquisition and decision output, verbal protocols used in the second study provided more direct access into the thought processes underlying the analysts' decision strategies.

We used a standard approach for concurrent verbal reports, instructing subjects to think aloud while carrying out their decision process (Ericsson and Simon 1993). If appreciable periods of silence (e.g., 5–10 seconds) occurred, the experimenter encouraged verbalization by prompting with a simple "keep talking" or "what are you thinking about now?" Studies have shown that, when properly administered, think-aloud procedures should not affect response accuracy (Ericsson and Simon 1993; cf. Biehal and Chakravarti 1989); however, they can require more time than studies without such requirements (Anderson 1985). For this reason, we provided the participants with the stock information on sheets of paper rather than on a computer screen to facilitate the speed with which they could complete the task. Two practice tasks in unrelated decision-making domains were completed prior to participation in the investment simulation to familiarize subjects with the procedure.

Subjects

We recruited a snowballing convenience sample of nine participants (eight males, one female) by contacting graduate business school alumni of two large eastern universities. All participants were working as security analysts in major metropolitan areas. For participation, each subject received $100 as well as the chance for publicity in a press release. The mean age of the participants in this study was 32.8 years (range: 25–45). On average, the analysts had 2.9 years of experience as a security analyst, and they earned a mean return of 34.1% (range: +6.2% to +100.9%) on their investment portfolios over the course of the simulation. Thus the analysts in this study were about the same age as those in study 1, but on average they possessed less work experience and earned slightly higher returns.

Decision Task

The procedure for this study was identical to that of the first study, with three exceptions. First, the analysts were instructed to think aloud while making their investment decisions. These verbalizations were tape recorded for later transcription and analysis. Second, to facilitate task completion in a timely manner, the stock information was presented to the analysts on sheets of paper, period by period, rather than on a computer screen. Third, at the end of the stock-picking simulation, the analysts took part in a depth interview. The analysts took from one to two hours to complete the study.

Results

We classified the analysts on the basis of their behavioral reactions to price changes of stocks in their portfolios as in study 1 and determined that five of the nine analysts clearly exhibited either a momentum or contrarian strategy. These five were retained for further analysis. The qualitative analysis of the verbal protocols involved multiple readings of the transcripts (Strauss and Corbin 1998). Differences in interpretation were discussed and resolved. The results of an idiographic analysis (Mick and Buhl 1992) are provided below.

John—the High Roller. John, in his thirties, had worked in the field for three years. He was clearly a momentum investor, based on his responses to price changes of stocks in his portfolio. His thought verbalizations, however, revealed a unique variation of the momentum strategy. He achieved the highest raw return (100.9%) by investing only in the smallest firms with positive momentum. He first divided the six stocks into small-, medium-, and large-sized firms and ruled out the larger firms for investment because they would not help him sufficiently to "capture the upside."

John was clearly not afraid of risk. He consciously sought it out, stating, "since we are just trying to maximize the upside here, more volatility is actually a good thing." And further, "the smaller the better, and the more potential volatility the better." In terms of hedging his bets with cash, he stated, "I don't want any cash. It is not going to help me maximize my returns." John was not concerned with creating a diversified portfolio to minimize risk: in the last period of the simulation, he bet his entire portfolio on a single stock, A, a small-cap stock that exhibited large price swings over time, explaining:

> Besides looking at the price and momentum, really, I find myself not using much of anything else. . . . Alright! Hey, how about that? I am doing well! I bet on the right horse, man. I am really totally in the dark—the joy of being a momentum player. I think A is going to do well. I think A turned the corner. I am going to put a lot on A to get a maximum return. . . . I know looking through this balance sheet information really would not help me. . . . I am going to move everything to A. . . . I think it is a small company that has some kind of technology, and it's finally being recognized. And it is small, so it has a lot of upside. T is already a medium-sized, small- to medium-sized, company. It's turning the corner but it's not as exciting as A. I think A would

> have more upside. OK, everything. I am just going to bet the ranch. T would be a very good bet also, but I think that A has more potential. A has more potential. It's a lot smaller. It's high risk, high return, more upside.

John used a simple decision heuristic—follow price trends and focus on firm size. He did not integrate much other stock information. In the depth interview, he explained: "In general, my strategy is to put all eggs in one basket. I always pick one stock that I really like and follow that stock very carefully. I put almost all my money in that one stock. It is very risky, but in my mind, it is not any more risky than spreading them out and not really knowing all the stocks."

Stuart—the Chartist. Stuart, in his twenties, had 4.5 years of experience in the domain and also exhibited a momentum-based pattern of responses. He explained his approach by saying, "I'll just put down the high, low, and close and the change for the quarter because I think, at the end of the day, price is one of the most important factors because if you buy something and it goes up, whether the fundamentals are great or they stink, if it's up, you're ahead." He states more directly that "I am going to play a momentum game here" and that "I am not going to fight the price trend." In the depth interview, Stuart confirmed his belief in a momentum strategy and offered anecdotal evidence in support of it, despite his acknowledgment of research to the contrary. "If [a stock price] has fallen, it will go lower. If it is going up, it will go higher. Buy if it hits a new high, and buy on a breakout. Sell when it hits a new low. That I definitely agree with. . . . I have done studies at [MBA school] with this, and the real answer [to serial correlations] is 'no.' But look at something like GE or Cisco that is going up and up over 10–15 years. There is a reason it has done that. . . . I like to buy stocks that have up trends."

Stuart differed from other momentum investors in that he was constantly on the lookout for peaks and troughs in the price trends he followed. Thus, he believed the trajectories could change direction, and his major efforts were devoted to spotting those turnaround points.

> The first thing I am going to do is check out the price change here—seeing that the two stocks that performed the best last quarter, which were C and L, once again performed the best . . . I will put in a high/low/close for these issues. Now I am going to compare high/low/close from the previous quarter to see where we are at and also the price change. Are we setting new lows? In the case of A, we did set a new low. . . . Looking at L . . . Closed once again at $3.94, near your high of $4.00. Looks like momentum is continuing there. The one prior to that closed at $5.22; it was up to $5.84, so you did see it back off 10% from its high. The first one is down significantly from its high of $9.75, finished at $5.75, and you were down from $4.63. It's almost a 50% drop from your high. So now let's go on to I, where we had a 16% decline, and we look here at the close. You closed at the low of the quarter—never a good sign. Also, the high for the quarter was 10% above, but it really looks like this thing backed off at the end of the quarter. This is coming on top of a 19% decline. . . . Looks like the downside, the momentum, has increased.

Stuart thus exhibited a momentum approach supplemented by a peak/trough search. He generally assumed stock prices would continue to move in the same direction they had been moving in, unless he saw signs indicating the stock was reaching a peak or trough. In that case, he would shift his expectations toward a price reversal. In the depth interview Stuart explained how he did this: "Compared to a lot of other analysts, I think I am a lot more graphic. I like to see things graphically. I would like to take these numbers graphically and see your trends. I really think it helps to see the picture as opposed to looking at the numbers."

Indeed, of all the analysts, Stuart took the longest amount of time, about two hours, to complete the simulation, creating a detailed spreadsheet to visualize price peaks and troughs. He explained: "I am putting in here the high/low/close and quarterly change. What I want to do, once I get this whole thing together is compare. I think it will be easier to visualize it by laying it out like a spreadsheet format. You know, which direction the stock is moving in, is it closer to its high, is it closer to its low, what did the stock do that quarter? What did it do the quarter after? God, this sounds very technical, I'm sure."

Interestingly, like John the High Roller, Stuart the Chartist also decided to move all of his assets into a single stock (I) in the fourth quarter of the game. In Stuart's case, however, it was not on the basis of positive portfolio feedback. Instead, it was because he seemed to have lost faith in his technical analysis:

> Oh, I'm going to lose my job if I keep this up. OK, what happened here with D? The flat sales—I shouldn't have gone for it. I saw the income pop up. I am doing worse quarter to quarter. Better when I had less information. Of course, I sold A, and that is up 19%. And L, if I would have stuck with those. . . . I am a quarter early, that's my problem. I am going to fill in high/low/close right now for these. See if we could figure out something. Try to save my job here. Maybe I will have another good quarter. Now I will look at the percentage change here. Percentage change in price. Great—if I had A, B, and C, I would have been set. I think this time what I am going to do is go with the opposite of what I think. Then maybe I will make a fortune. . . . I am not touching L—it's up another 33%. It has topped out. It's history. It's done. . . . [Stock] I was up 11%, sales have been climbing each quarter. To me, this one is due to go. I don't know why it's doing so poorly. K, this thing just doesn't do anything—not enough volatility. Stay away from that since we want to make money here. And D, all this thing does is go down. . . . Looking at C right now . . . the stock had its move. I think I will stay away from C because it looks like the sales momentum has really dried up. Go back to A. A is losing money, sales are dropping, yet the stock recovered. I am going to stay away. I am staying away from A. [Stock] I looks interesting. The first two quarters [stock]

> I lost money, the last two they made money. Sales have been growing sequentially, which I like. That is a possibility. K has not been good luck for me. I am staying away from it even though sales have been going up nicely. And D, this has been down the last four quarters, but I am not going to fight that. I am not going to catch a falling sword. I am going to put all my money in [stock] I. . . . All or nothing here.

Thus, Stuart was willing to abandon his momentum strategy when it produced lackluster results. In the end, he earned a raw return of 6.2%.

Karen—Searching for Growth. Karen, a female analyst in her thirties, had been working as a security analyst for just six months when she took part in the stock-picking simulation. She would be categorized as a momentum investor based on her responses to price changes of stocks in her portfolio. Her momentum orientation was revealed early in the simulation when she made her allocation decisions for the first period, saying, "And how I'm doing this is, I'm really going off of the price change in the quarter." Not surprisingly, Karen's stock-picking strategy focused on firms' growth potential. However, she also revealed a slightly unique aspect to her momentum strategy in that she did not use simply stock price advances to evaluate growth opportunities: "I like to pick stocks in markets that are growing. . . . The companies that make [technical software] are all pretty much the same. They have the same kind of people, blah blah blah. So what I do is, I go and say, OK, which one of these guys has the most growth prospects? And then I start from there, and then I analyze the companies."

Karen, who earned a raw return of 28.3%, was like the other momentum analysts in that she was fairly confident about her ability to choose stocks for investment that would beat the market: "I like to think of companies as little black boxes that make money. Money comes in, money leaves them, and then they get bigger based on the money they keep. I think that's why people buy stocks—because they're badder at keeping the money that's going through them than not keeping. So I think that sure, if you can pick these good companies that keep the money and have the products, then you can beat the market."

David and Bruce—Disciplined Fundamentalists. David, an analyst in his thirties, would be categorized as a contrarian investor on the basis of his responses to decision feedback. He achieved a raw return of 7.14%. He stated in the interview that his approach to evaluating stocks for investment is "pretty fundamental based" and that he considers himself to be a contrarian investor. Not surprisingly, he agreed that "the market does overreact to negative news" and spoke about the role of "investment psychology." David's verbalizations regularly exhibited expectations of price reversals and preferences for stocks whose prices had recently fallen. Among the 23 fundamental factors provided in the simulation game, David paid special attention to those related to liquidity (e.g., sales, receivables, and inventory). He conducted a considerable number of calculations during the simulation in an attempt to arrive at a more accurate estimate of firm value. For example: "I am just going to calculate the sales, receivables as a percentage of sales, and percentage of sales to inventory—to give me an idea of how well these guys are moving product out. Maybe there is a collection issue. Just calculating the sales to the receivables to get an idea of what % of the sales are tied up in receivables. Okay . . . I do not like A. Receivables exceed sales. They also have a decent amount of inventory, and the stock has been paying the price for that. So I will shy away from A."

Unlike the momentum investors, David did not like stock A, which exhibited large and rapid price increases that he did not believe were justified on the basis of his fundamental analysis. David invested the largest share of his portfolio in stock D, whose price fell fairly consistently during the course of the simulation. David continued to increase his exposure in that stock throughout the simulation, expecting it to rebound. His remarkable commitment to stock D in spite of repeated price decreases can be seen in these comments: "Hmmm, I still think D should do OK in through here. D still has a decent amount of assets, positive earnings, is paying out dividends. Long-term debt is fairly modest. Inventories aren't too bad versus sales. I still think that D is the way to go." Then, after learning about another fall in D's price he states: "D continues to hurt me. D has cost me some money here. . . . What's the deal with D here? Everything still looks the same in D. Not much improvement quarter to quarter. They still have some cash. Receivables and sales are still only about 2/3. The price is down 19% again, and the net income is still positive. The inventory is still around 31 million. . . . Same dividends as the last time. They still have some cash, and assets are pretty good. D continues to look good to me."

After the last period of the simulation, David states:

> Wow, I got D wrong the whole way. D, you are hurting me. Let's see here, what were the returns? A, wow, A, good quarter even though sales have declined. Wow, I don't understand why it was up 20%. C was down 10%. L was up 33%. L has been the big winner here. T was up 11%. K is negative and D again negative. I cannot figure out why D is not performing well. . . . I continue to like D. I will still go with D. Should I continue down that path? I guess D is pretty high leverage here. . . . I continue to like D. It's my last go here. We've gone the whole way here, so let's go all the way.

David maintained a disciplined contrarian orientation even in the face of lackluster results.

For similar reasons we label Bruce, an analyst in his thirties with 8.5 years of experience in the domain, a "disciplined fundamentalist." Bruce earned a raw return of 27.8%. Like David, Bruce would be categorized as a contrarian investor based on his investment decisions after feedback. Also like David, he exhibited a clear tendency to conduct fundamental analysis calculations and to make his decisions accordingly. However, unlike David, Bruce's focus was on two other metrics: earnings per share and price/earnings ratios.

Bruce described his stock-evaluation strategy as consisting of factors somewhat broader than just price movements:

> I consider the strength of a product and management first, and then I consider the value the market places on those two. I feel that a good product, a company with a good product, will do well. And a company with a good management should do well because they can always change their product if they have to or change it in order to make it successful. Good management recognizes that, but then there's a price the marketplace puts on that, and if I think that it's cheap, I'll buy it. If it's underpriced, I'll buy it. If it's overpriced, I'll sell it.

Like David, Bruce grew to dislike stock A because it had insufficient earnings. Indeed, his initial portfolio was invested in every stock except that of stock A, a favorite of some of the momentum investors. Also, like David, he continued with his basic investment strategy despite negative feedback on prior decisions. For example, in a later period of the simulation he states, "It's obviously hurt me every time taking money out of Company L. That's been the biggest winner. But let's stick with the discipline. . . . Calculate the earnings per share."

DISCUSSION

The findings from both studies reported here suggest that the security-analysis decision-making process is heterogeneous and multifaceted but not random in nature. In both studies, two distinct information-processing and decision-making styles emerged: momentum and contrarian. These two types of investors differed on a number of dimensions. Most notably, they inferred opposite meanings from price changes of stocks held in their portfolios. Momentum investors generally expected recent stock price trends to continue. Momentum investors favored growth stocks, those that had been exhibiting continued price increases, whether or not the increases were justified by economic fundamentals. Idiosyncratic variations of this theme emerged, such as a focus on small-cap stocks or a search for peaks and troughs. The contrarians expected stock price reversals. They typically divested themselves of stocks they owned whose prices had risen and bought more of stocks they owned whose prices had fallen. The contrarians looked for bargains, stocks they believed to be temporarily undervalued due to the market's overreaction to negative news, and they avoided glamour stocks, those they believed were overvalued, as indicated by fundamental factor analysis. Idiosyncratic variations of this core strategy were evident in terms of the metrics deemed most relevant to assess firm value (e.g., liquidity vs. earnings measures).

The momentum and contrarian investors' cognitive-processing styles also differed. The momentum investors used a relatively simple decision heuristic (i.e., follow current price trends) to predict future stock prices. The contrarian investors elaborated more on each item of stock information accessed to construct ratios to assess value and predict future prices.

Momentum and contrarian investors differed in terms of risk propensity. Momentum investors generated higher raw performance by deliberately constructing more volatile stock portfolios. They exhibited little interest in portfolio diversification to reduce risk. The contrarians avoided the smallest, most volatile stocks and were willing to trade off potential return for reduced risk.

There was also evidence that the momentum and contrarian investors differed in the degree to which they were willing to adapt their decision strategy over time. The contrarians were committed to maintaining their value-based stock-picking strategy, even in the face of poor performance. The momentum investors exhibited greater willingness to switch strategies midstream should the approach not appear to be performing as well as desired. Contrarian investors may thus be less susceptible to style drift or the tendency for investors to shift their strategies over time.

Finally, momentum and contrarian investors differed in their decision confidence levels. The momentum analysts believed they could beat the market, that is, systematically earn higher than average returns on their stock investments (Stuart: "I think you can definitely do that." John: "I think so." Karen: "Oh yeah!"). Although the contrarians also agreed it was possible to beat the market, they thought it might be more difficult than the momentum analysts (David: "I think it is getting more difficult, since information can be found very fast and everyone gets the information at pretty much the same time these days."), or they had doubts about their own ability to do so (Bruce: "I think it's possible. I don't think it's possible for me."). If it is true that momentum investors' performance, when adjusted for risk, does not exceed that of the contrarians, then the momentum investors' greater confidence levels may make them more susceptible to what Alba and Hutchinson (2000) term "knowledge miscalibration," a mismatch between decision confidence and decision accuracy. The extent of knowledge miscalibration may be related to the investors' relative experience in the domain. There was some evidence that the momentum investors were not only younger and less experienced than the contrarians but also that they were less likely to have personally experienced a significant downturn in the market. Since knowledge calibration is a function of remembering the past, interpreting the present, and predicting the future (Alba and Hutchinson 2000), the momentum investors' lesser investment experience may provide them with a weaker basis for learning and extrapolating from past experience.

Implications

Implications for Financial Decision-Making Theory. Behavioral finance theorists have not yet formulated a comprehensive theory to assimilate the various anomalies they have noted in the stock market. Statman (1999) provides a potential basis for a unifying framework by making a clear distinction between two separate implications of efficient-market theory: (1) investors cannot systematically beat the market, and (2) stock prices are rational. We have, in the research presented here, found evidence for the first of these implications but not necessarily for the second. Our research indicates that although individual behavior often diverges from rationality, none of the major behavioral patterns observed was capable of producing supranormal returns (when adjusted for risk). This result is in accord with traditional finance theory. However, it does seem possible that individuals' biased behaviors have the potential, in the aggregate, to create asset prices that deviate from their rational or true economic values. It is important to note that the individual investors' behavior patterns in our studies did not vary in a random fashion. If this had been the case, then we might conclude that the various irrational approaches to investment decision making by individuals likely cancel each other out at the aggregate level, in terms of impact on stock market prices, and thus result in an efficient market. Instead, what we observed was that most investors tended to exhibit either momentum or contrarian responses to portfolio price changes. Thus most investors were acting in concert with a group of like-minded individuals. If a large and growing number of decision makers were to adopt a particular investing style, this could create a market anomaly such as a run-up (or fall) in stock prices unsupported by financials. So, although in our research stock prices were constrained from influence by the participating analysts, in the real world, sizable group preferences for either growth stocks (e.g., momentum investors) or value stocks (e.g., contrarian investors) could presumably cause such assets' price levels to deviate from rational values. Indeed, a herd-based, momentum-style contagion seems to have been partly responsible for the recent Internet stock bubble (of 1999–2000). Our conclusions regarding a potential basis for the reconciliation of behavioral finance with the traditional paradigm are therefore congruent with those of Statman (1999), who proposes that market efficiency may be true insofar as there are no systematic ways to beat the market but not necessarily in terms of asset-pricing rationality. Asset-pricing models would thus seem to be the element of traditional finance that would most benefit from incorporation of an understanding of individual decision-making psychology.

Implications for Novice Consumer Investors. Bazerman (2001, p. 499) recently called for more consumer research about decisions involving important purchases "to help consumers think clearly and abstractly about the toughest buying decisions," such as those involved in financial services and investment. Such a call seems timely as it has been reported that consumer confidence in stock brokers has declined substantially from the mid-1960s to the present time (Shiller 1993). Our research represents a critical first step in this direction. Our results suggest that when choosing decision-making agents in this domain, consumers should understand that many analysts tend to exhibit distinct portfolio price–driven strategies (e.g., momentum or contrarian) and that these tendencies may be associated with age and experience in the domain, as well as risk propensity, overconfidence, and style drift. Ideally, a novice consumer investor choosing an analyst for investment advice should choose an analyst whose market philosophy matches his or her own.

Limitations

The findings reported here are limited in at least two major respects. First, the conclusions are based on the behavior of small samples of security analysts working in eastern U.S. metropolitan areas. Thus, it is not certain to what degree the current set of results holds true for the entire population of security analysts. Second, certain aspects of the simulation may have constrained the analysts' natural behavior patterns and thought processes. For example, the analysts were instructed to ignore transaction costs and were given a single goal, to maximize return—situational factors that do not perfectly reflect real world settings. In addition, the analysts had access to only limited types of information and were not permitted to confer with other analysts as they might normally do before making actual investment decisions. Such constraints may have caused the analysts to engage in more simple and extrapolative decision strategies than they normally would in real life. Analysis of actual portfolio decisions by professional analysts would greatly help in determining the extent to which the experimental constraints in our research may have impacted analysts' natural behavior patterns.

[*Received July 1999. Revised November 2001. David Glen Mick served as editor and Michael D. Johnson served as associate editor for this article.*]

REFERENCES

Alba, Joseph W. and J. Wesley Hutchinson (2000), "Knowledge Calibration: What Consumers Know and What They Think They Know," *Journal of Consumer Research*, 27 (2), 123–156.

Anderson, Matthew J. (1985), "Some Evidence on the Effect of Verbalization on Process: A Methodological Note," *Journal of Accounting Research*, 23 (2), 843–852.

Basu, Sanjoy (1977), "The Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis," *Journal of Finance*, 32 (3), 663–682.

Bazerman, Max H. (2001), "Consumer Research for Consumers," *Journal of Consumer Research*, 27 (March), 499–504.

Biehal, Gabriel and Dipankar Chakravarti (1989), "The Effects of Concurrent Verbalization on Choice Processing," *Journal of Marketing Research*, 26 (1), 84–96.

Bodie, Zvi, Alex Kane, and Alan J. Marcus (1999), *Investments*, 4th ed., Boston: McGraw-Hill.

De Bondt, Werner F. M. and Richard H. Thaler (1985), "Does the Stock Market Overreact?" *Journal of Finance*, 40 (July), 793–805.

Ericsson, K. Anders and Herbert A. Simon (1993), *Protocol Analysis: Verbal Reports as Data*, Cambridge, MA: MIT Press.

Graham, Benjamin and David L. Dodd (1934), *Security Analysis*, New York: McGraw-Hill.

Jacoby, Jacob, James J. Jaccard, Alfred Kuss, Tracy Troutman, and David Mazursky (1987), "New Directions in Behavioral Process Research: Implications for Social Psychology," *Journal of Experimental Social Psychology*, 23 (2), 146–174.

Jacoby, Jacob, Alfred Kuss, David Mazursky, and Tracy Troutman (1985), "Effectiveness of Security Analyst Information Accessing Strategies: A Computer Interactive Assessment," *Computers in Human Behavior*, 1 (1), 95–113.

Jegadeesh, Narasimhan and Sheridan Titman (1993), "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, 48 (1), 65–91.

Mick, David Glen and Claus Buhl (1992), "A Meaning-Based Model of Advertising Experiences," *Journal of Consumer Research*, 19 (December), 317–338.

Ou, Jane A. and Stephen H. Penman (1989), "Financial Statement Analysis and the Prediction of Stock Returns," *Journal of Accounting and Economics*, 11 (4), 295–329.

Punj, Girish and David W. Stewart (1983), "Cluster Analysis in Marketing Research: Review and Suggestions for Application," *Journal of Marketing Research*, 20 (May), 134–148.

Sharpe, William (1964), "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," *Journal of Finance*, 19 (3), 425–442.

Shefrin, Hersh M. and Meir Statman (1993), "The Disposition to Sell Winners Too Early and Ride Losers Too Long," in *Advances in Behavioral Finance*, ed. Richard H. Thaler, New York: Sage, 507–525.

Shiller, Robert J. (1993), "Stock Prices and Social Dynamics," in *Advances in Behavioral Finance*, ed. Richard H. Thaler, New York: Sage, 167–217.

Statman, Meir (1999), "Behavior Finance: Past Battles and Future Engagements," *Financial Analysts Journal*, 55 (6), 18–27.

Strauss, Anselm and Juliet Corbin (1998), *Basics of Qualitative Research*, 2d ed., Thousand Oaks, CA: Sage.