

BEHAVIORAL FINANCE: LEARNING FROM MARKET ANOMALIES AND PSYCHOLOGICAL FACTORS

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Abstract: Empirical research has shown that, when selecting a portfolio, investors not only consider statistical measures such as risk and return, but also psychological factors such as sentiment, overconfidence and overreaction. In short, heuristic-driven bias, frame dependence, and market inefficiency shape the kind of portfolios that investors chose, the type of securities investors find attractive, and the biases to which investors are subject. As a consequence, the purpose of the paper is to identify those psychological factors that play an important role in their decisions. Specifically, the paper reviews the existing literature on overconfidence and overreaction, defining the factors, analyzing their implications, identifying questions that have been left unanswered, and addressing the implication of these factors on market efficiency and investors' rational behavior. Finally, and in trying to contribute to the theory of Behavioral Finance, some future steps and research are proposed.

Introduction

Traditional Portfolio Theory believes in efficient markets, which means that the prices of the securities coincide with their fundamental value. As maintained by the efficient market school, investors are rational; i.e. their investment decisions are made according to their risk aversion, which is measured by the mean and variance of the returns. One of the pillars of standard finance

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was developed by Harry Markowitz, who developed the theory of mean-variance portfolios, offering a frontier of efficient portfolios with different risk-return combinations from where investors can choose given their risk aversion.

However, the major factors driving portfolio selection are much more complex than the mean and variance of future returns and the efficient frontier. Over the last 25 years, scholars began to discover empirical results that were not consistent with the view that market returns were determined in accordance with the efficient market theory. Additionally, empirical research shows that, when selecting a portfolio, portfolio managers not only consider statistical measures such as risk and return, but also psychological factors such as sentiment, overconfidence, overreaction, etc. As these factors began to be identified by scholars, a new school of thought began to emerge; that of Behavioral Finance.

Behavioral Finance (BF) is the application of psychology to financial behavior; i.e. it is the behavior of practitioners. According to BF, investors are rational, but not in the linear and mathematical sense based on the mean and variance of returns. Instead, investors respond to natural psychological factors such as fear, hope, optimism and pessimism. As a result, asset values may deviate from their fundamental value and the theory of market efficiency suffers.

Empirical research has shown that these behavioral factors do exist and that they are, in fact, considered by the market. Thus, this may imply that the market goes beyond the traditional theory of finance. In short, heuristic-driven bias, frame dependence, and market inefficiency shape the kind of portfolios that investors chose, the type of securities investors find attractive, and the biases to which investors are subject.

As a result, the purpose of the present paper is to identify not only the statistical measures that influence investors' decision making, but also the psychological factors that play an important role in their decisions. Specifically, the paper will review the existing literature on two of the main behavioral factors that affect portfolio selection, analyzing if the factor and its implications have correctly been defined, and identifying

questions that have been left unanswered. In particular, the paper will address overconfidence and overreaction and their implication on market efficiency and investors' rational behavior. Finally, some future steps will be proposed.

The structure of the paper is as follows: Section I explains briefly the assumptions underlying Traditional Portfolio Theory; Section II concentrates on Behavioral Finance and its beginnings; Section III reviews the literature on overreaction and overconfidence, concentrating mainly on empirical research; Section IV discusses the implications for market efficiency and investors' rational behavior as well as the responses given by the Traditional Finance Theory, and Section V proposes some future steps for research.

I. Traditional Portfolio Theory

The beginning of Standard Finance is generally considered to be the publication of "Portfolio Selection" by Harry Markowitz in 1952, who described how rational investors should create portfolios given a set of return expectations, volatilities and cross correlations. A rational investor maximizes expected returns and minimizes risk. The investor is pressured by two opposing forces: the desire to make earnings and the dissatisfaction produced by risk. In this way, risk and return are the two key features of investment strategy, where risk is measured as the average (or mean) absolute deviation and the standard deviation (Sharpe, 1985).

In order to select portfolios, the model requires the following information: (1) expected returns of the assets; (2) standard deviation of each asset; and (3) covariance between the returns of every pair of assets. Given this information, it is possible to construct an efficient portfolio frontier.

A portfolio is efficient when it offers the highest return given a specific risk, or the minimum risk given a specific return. Consequently, the group of efficient portfolios can be determined by solving one of the following two problems:

a. Maximize expected return of the portfolio for a given portfolio risk:

$$E[R_p] = X_1 E[R_1] + X_2 E[R_2] + \dots + X_n E[R_n]$$

Subject to: $\sigma_p^2 = \sum_i \sum_j X_i X_j \sigma_{ij} = V^*$

$$X_1 + X_2 + \dots + X_n = 1$$

$$X_1, X_2, \dots, X_n \geq 0$$

b. Minimize portfolio risk for a given portfolio expected return:

$$\sigma_p^2 = \sum_i \sum_j X_i X_j \sigma_{ij}$$

Subject to: $E[R_p] = X_1 E[R_1] + X_2 E[R_2] + \dots + X_n E[R_n] = R_p^*$

$$X_1 + X_2 + \dots + X_n = 1$$

$$X_1, X_2, \dots, X_n \geq 0$$

The portfolios on the frontier are efficient in the sense that they offer the highest $E[R_p]$ for each value of σ_p , or the lowest σ_p for each value of $E[R_p]$.

But in order to determine the “optimal” portfolio for the investor, it is necessary to understand the investor’s utility function, expressed as indifference curves. The rational investor will choose assets that offer high expected returns and low risk (it is assumed that all investors are risk averse). As a result, the investor’s utility function (μ) is defined as follows:

$$\mu = F(E[R_p], \sigma_p^2)$$

$$\partial \mu / \partial E[R_p] > 0$$

$$\partial \mu / \partial \sigma_p^2 < 0$$

Finally, the tangent point between the investor’s indifference curves and the efficient frontier, will determine the desired risk-return combination. Once this portfolio is selected, it is possible to obtain the percentages to invest in each of the assets that form the portfolio (X_i).

Markowitz’s main contribution was suggesting that the stock’s risk should be evaluated not in isolation, but also in terms of its contribution to the risk of a diversified portfolio. He showed how an investor can reduce portfolio

risk by choosing stocks that do not move together; i.e. that they are not affected by the same factors. In statistical terms, this means that stock prices are not perfectly correlated and risk can be eliminated through diversification.

Sharpe (1964) extended the original work of Markowitz and developed the Capital Asset Pricing Model (CAPM). Sharpe incorporated the Markowitz mean-variance-optimizer investor as well as the concept of efficient markets. The CAPM assumes that individuals are identical in expectations, investment horizon and access to available securities. Additionally, it assumes that individuals can borrow and lend at the same interest rate, the risk-free rate (R_f). As a result, some combination of R_f and the tangency efficient portfolio will offer a better risk/reward trade-off, at every level of risk, than other points on the Markowitz efficient frontier. Since there is only one risky portfolio that is held by all rational investors, that portfolio must be the market (Fabozzi, 1998).

This theory is also based on the assumption that markets do not compensate investors for assuming risk that can be reduced or eliminated through diversification. Total risk is considered to be the sum of systematic and unsystematic risk. Systematic risk, measured by beta, captures the reaction of different individual securities or portfolios to changes in the market portfolio. This risk cannot be eliminated through diversification because securities' prices tend to move, to a certain extent, with the market (there are several macroeconomic variables that affect, to a more or lesser extent, all industries and, consequently, stocks tend to move in the same direction).

On the other hand, unsystematic risk reflects the variability in the prices of the securities due to factors which are internal to the firm or to the industry in which the firm operates. As a result, as the CAPM sustains that investors will receive higher returns only if they assume higher systematic risk, and as beta is the indicator of systematic risk, the return of the securities is a linear function of beta (Gonzalez Isla, 2006).¹

To sum up, the main implications of the CAPM are that (1) the market portfolio is mean-variance efficient; and (2) the average return is an increasing function of beta.

Efficient Market Hypothesis

Traditional Finance assumes market efficiency. Although Fama officially introduced the notion of an “efficient” market in 1965, the empirical research that preceded the efficient market hypothesis modeled price behavior in statistical terms, and it received the name of “random walk hypothesis”. Under the assumptions of this hypothesis, successive daily stock price changes were independent; i.e. they displayed no discernable trends or patterns that could be exploited by investors (Ball, as cited in Chew 1999). In other words, random walk means that no prediction of the future movements can be made based on historic information.

Fama (1965) defined an efficient market as one ‘where there are large numbers of rational, profit-maximizers actively competing with each other, trying to predict future market values of individual securities, and where important current information is almost freely available to all participants’. As a result, a market is efficient with respect to an information set if it is impossible to earn consistent abnormal profits by trading on the basis of the information set (Daniel, 2002).

Three types of market efficiency have been identified:

Weak: market efficiency in its weak form means that no investor can earn consistent abnormal profits trading on the basis of past- price information; that prices reflect all the information contained in historic prices. Some implications of weak form efficiency are that technical analysis is not profitable as there is no price momentum or price reversal.

Semi-strong: market efficiency in this form means that no investor can earn consistent abnormal profits trading on any public information; i.e. that prices not only reflect historic prices, but also any additional public information (such as earnings announcements, dividends, etc). Implications of semi-strong form efficiency are that fundamental analysis and trading based on the published earnings forecasts or analysts’ reports are not profitable.

Strong: market efficiency in its strong form means that no investor can earn consistent abnormal profits trading on the basis of any information,

private or public. An implication of strong form efficiency is that insider trading is not profitable.

In an efficient market, the changes in prices are random, because if prices always reflect all the relevant information, they will only change under new information (by definition, new information cannot be anticipated). Consequently, changes in prices cannot be predicted. In other words, if prices already reflect everything that is “predicted”, then changes in prices must only reflect the “unpredictable”. In a perfectly efficient market, prices will always equal fair values.

In regards to the accomplishment and limitations in the theory of Efficient Markets and Rational Investors, a large body of empirical research in the 70's provided evidence of market efficiency that offered strong support for the CAPM and the models that followed, such as the Arbitrage Pricing Theory and Option Pricing models. However, and in spite of all its accomplishments, the efficient markets theory also had its setbacks. After a period in which one triumph of modern financial theory succeeded another, research began to accumulate evidence of “anomalies” that appeared to contradict the theory of efficient markets (Chew, 1999).

Additionally, the theory of rational behavior also began to suffer. Most recent literature identified under the concept of Behavioral Finance, shows that investors behave in a non-rational way. Jensen (as cited in Chew, 1999) describes non-rational behavior as the behavior that ‘arises under conditions of fear’. While attempting to avoid the pain associated with acknowledgments of their mistakes, people often end up incurring more pain and making themselves worse off. Jensen believes that this non-rational behavior is not random. LeDoux (1994) suggests that such counterproductive defensive responses derive from the biological and chemical structure of the brain, and are connected to the brain’s “fight or flight” response. The mechanisms of the brain commonly blind people so that they are unaware of their own fear and defensiveness. And the primary consequence of such defensiveness is the reluctance of people to learn and their resulting inability to respond properly to feedback and change (Jensen, as cited in Chew 1999).

Finally, investors recognize that due to the inefficiency present in financial markets, prices may not be correctly reflecting all the information available; i.e. some securities may be over or undervalued. It is the portfolio manager's job to identify these opportunities and adopt an investment strategy accordingly.

II. Behavioral Finance

Behavioral finance (BF) is the application of psychology to financial behavior, the behavior of practitioners. Even though the idea that psychology plays an important role in investors' behavior became popular only recently, several economists and psychologists have been trying to integrate these fields for quite some time.

Keynes wrote of the influence of psychology in economics more than fifty years ago. Additionally, psychology Professor Paul Slovic published a detailed study of the investment process from a behavioral point of view in 1969. However, it was not until the late 1980s that BF began to get acceptance among professional economists. At that time, Professors Richard Thaler at the University of Chicago, Robert Shiller at Yale University, Werner de Bondt at the University of Illinois, and Meir Statman and Hersh Shefrin at Santa Clara University, among others, began to publish research relevant to Behavioral Finance (Olsen, 1998).

These scholars began to discover a host of empirical results that were not consistent with the view that market returns were determined in accordance with the CAPM and the efficient market hypothesis. Proponents of Traditional Finance regarded these findings as anomalous, and thus called them anomalies. BF's main contribution was to allow a better understanding of the anomalies present in investors' behavior by integrating psychology with finance and economics. However, it was not until Professor Daniel Kahneman of Princeton University was awarded the 2002 Nobel Prize in economic sciences that BF gained momentum.² Consequently, it was not until researchers began to discover empirical results that were not consistent with the efficient market theory that BF became popular. In

short, the growing interest in BF has been the result of an accumulation of empirical anomalies.

Shefrin (1998) categorizes the behavioral factors identified throughout the years into three broad themes:

Heuristic-driven bias: The dictionary definition for the word heuristic refers to the process by which people find things out for themselves, usually by trial and error. Trial and error often leads people to develop rules of thumb, but this process often leads to other errors. As a result, BF believes that practitioners commit errors because they rely on rules of thumb; BF recognizes that practitioners use rules of thumb called heuristics to process data. One example of rules of thumb is: 'past performance is the best predictor of future performance, so invest in a mutual fund having the best five-year record'. But rules of thumb are generally imperfect. Therefore, practitioners hold biased beliefs that predispose them to commit errors. In contrast, Traditional Finance assumes that when processing data, practitioners use statistical tools appropriately and correctly.

Frame dependence: BF postulates that in addition to objective considerations, practitioners' perception of risk and return are highly influenced by how decision problems are framed. In contrast, Traditional Finance assumes frame independence, meaning that practitioners view all decisions through the transparent, objective lens of risk and return.

Inefficient markets: BF assumes that heuristic-driven bias and framing effects cause market prices to deviate from fundamental values. In contrast, Traditional Finance assumes that markets are efficient, meaning that the price of each security coincides with fundamental value.

However, it is important to highlight that only the first two themes - heuristic-driven bias and frame dependence- are form of biases, while the theme regarding inefficient markets is a result of bias.

As Shefrin (1998) also summarizes, the main empirical anomalies that affect investors' behavior and their financial decisions, and that have also led to a reevaluation of the efficient markets hypothesis, are:

Anchoring and adjustment (conservatism): Analysts who suffer from conservatism due to anchoring and adjustment do not adjust their earnings

predictions sufficiently in response to the new information contained in earnings announcements. Therefore, they find themselves surprised by subsequent earnings announcements.

Aversion to ambiguity: People prefer the familiar to the unfamiliar. The emotional aspect of aversion to ambiguity is fear of the unknown.

Disposition effect: According to the disposition effect, investors have great difficulty coming to terms with losses. Consequently, they are predisposed to holding losers too long and selling winners too early.

Emotional time line: It is important to discuss emotion while analyzing financial decisions because emotions determine tolerance for risk. According to psychologist Lopes (1987), hope and fear affect the way that investors evaluate alternatives. Lopes tells us that these two emotions reside within all of us, as opposite poles, and one of her contributions is to establish how the interaction of these conflicting emotions determines the tolerance towards risk.

Loss aversion and “get-evenitis”: Kahneman and Tversky (1979) studied how people respond to the prospect of loss. They find that a loss has about two and a half times the impact of a gain of the same magnitude and they call this phenomenon loss aversion (Prospect Theory).

Momentum: Momentum takes place when stocks that get recommended are those that have recently done well.

Overconfidence: When people are overconfident, they set overly narrow confidence bands. They set their high guess too low and their low guess too high. There are two main implications of investor overconfidence. The first is that investors take bad bets because they fail to realize that they are at an informal disadvantage. The second is that they trade more frequently than is prudent, which leads to excessive trading volume. Additionally, this behavioral factor can be related to another empirical anomaly: Betting on Trends. De Bondt (1993) reports that people tend to formulate their predictions by naively projecting trends that they perceive in the charts. Second, they tend to be overconfident in their ability to predict them accurately. Third, their confidence intervals are skewed, meaning that their best guesses do not lie midway between their low and high guesses.

Post-recommendation drift: When an analyst changes a recommendation, the market price immediately reacts to the announcement, but the adjustment continues for a substantial period thereafter, affecting market efficiency (market efficiency holds that prices adjust virtually immediately to new information; post-recommendation drift is not a property of efficient prices).

Regret: Regret is the emotion experienced for not having made the right decision. Regret is more than the pain of loss. It is the pain associated with feeling responsible for the loss. People tend to experience losses even more acutely when they feel responsible for the decision that led to the loss. Regret can affect the decisions people make, as they try to minimize possible future regret.

Representativeness and overreaction: This principle refers to judgments based on stereotypes. A financial example illustrating representativeness is the winner-loser effect documented by De Bondt and Thaler (1985, 1987). Investors who rely on the representativeness heuristic become overly pessimistic about past losers and overly optimistic about past winners. As a consequence, investors overreact to both bad and good news. Therefore, overreaction leads past losers to become underpriced and past winners to become overpriced.

Sentiment: Sentiment is the reflection of heuristic-driven bias.

Separate mental accounts: This occurs when two decision problems together constitute a concurrent package but the investor does not see the package; instead the choices are separated into mental accounts.

III. Main behavioral factors that affect financial decisions: overreaction and overconfidence

As mentioned in the previous section, empirical research has shown that the behavioral factors do exist and that they are, in fact, considered by the market. As a result, the purpose of this section is to review the psychological factors that play an important role in investors' decisions. In order to focus the study, De Bondt (1998) has been used to narrow the selection of empirical anomalies to two factors: overconfidence and overreaction. De Bondt identified and

reviewed four classes of anomalies regarding individual investors that have to do with: (1) investors' perceptions of the stochastic process of asset prices; (2) investors' perceptions of value; (3) the management of risk and return; and (4) trading practices.

De Bondt illustrated these anomalies with selected results from a study of 45 individual investors in the Fox Valley in Wisconsin (USA). The investors were recruited at a conference organized by the National Association of Investment Clubs in Appleton. Every investor personally managed an equity portfolio and the mean value of their financial portfolio was \$310,000 (excluding real estate). The investors also agreed to make repeated weekly forecasts of the Dow Jones Industrial Average (DJIA) and of the share prices of one of their main equity holdings; i.e. the study tracked the group's forecasts for the future performance of both the Dow Jones and their own stocks. The research took place between October 1994 and March 1995.

De Bondt's findings showed the following:

- (i) Investors were excessively optimistic about future performance of the shares they owned but not about the performance of the DJIA.
- (ii) They were overconfident in that they set overly narrow confidence intervals relative to the actual variability in prices. They set their high guess too low and their low guess too high. Additionally, the confidence intervals were asymmetric. The average investor imagined more downward than upward return variability. As a result, they found themselves surprised by price changes to their stocks more frequently than they had anticipated.
- (iii) Their stock price forecasts were anchored on past performance.
- (iv) They rejected the notion of risk that relied on whether the price of a stock moved with or against the market (they underestimated the covariance in returns between their portfolios holdings and the market index; i.e. they underestimated beta). Additionally, they discounted diversification; i.e. holding few stocks was a better risk management tool than diversification

In short, De Bondt's survey highlights two of the most important behavioral factors that have been affecting financial decisions over the years: overconfidence

and overreaction. Specifically, the survey informs us that individual investors display excessive optimism and overconfidence, and that they overreact to both bad and good news. These anomalies can widely be seen among investors' behavior and their impact on financial decisions is very strong. As a consequence, these anomalies constitute two of the main areas of interest that BF scholars have nowadays.

Consequently, this section focuses on the anomalies on overconfidence and overreaction, trying to (1) identify their main issues and propositions; (2) review the empirical models that were used; and (3) develop a strength and weakness analysis, discussing if the research designs were appropriate to measure the behavioral factor and if questions have been left unanswered.

Overconfidence

1) Identification of its main issues and propositions.

Psychological studies have found that people tend to overestimate the precision of their knowledge (Lichtenstein, Fischhoff and Philips, 1982), and this can be found in many professional fields. They also found that people overestimate their ability to do well on tasks and these overestimates increase with the personal importance of the task (Frank, 1935). People are also unrealistically optimistic about future events; they expect good things to happen to them more often than to their peers (Weinstein, 1980 and Kunda, 1987). Additionally, most people see themselves as better than the average person and most individuals see themselves better than others see them (Taylor and Brown, 1988).

In regards to financial markets, when people are overconfident, they set overly narrow confidence bands. They set their high guess too low and their low guess too high. There are two main implications of investor overconfidence. The first is that investors take bad bets because they fail to realize that they are at an informal disadvantage. The second is that they trade more frequently than is prudent, which leads to excessive trading volume (Shefrin, 1998). As a result, financial markets are affected by overconfidence. But how are markets affected by this overconfidence factor?

2) *Empirical models: research designs and methodology.*

Several finance researchers have focused their research on overconfidence; perhaps the work by Terence Odean can be considered as more explanatory.³ For Odean (1998) overconfidence is a characteristic of people, not of markets, and some measures of the market, such as trading volume, are affected similarly by the overconfidence of different market participants. However, other measures, such as market efficiency, are affected in different ways but different market participants. One of the most important factors that determine how financial markets are affected by overconfidence is how information is distributed in a market and who is overconfident.

Odean (1998) examined how markets were affected by studying overconfidence in three types of traders: (i) price-taking traders in markets where information was broadly disseminated; (ii) strategic-trading insider in markets with concentrated information; and (iii) risk-averse market makers. In particular, he analyzed market models in which investors were rational in all aspects except in how they valued information. Additionally, the paper differed from related work on overconfidence in the sense that it examined how the effects of overconfidence depended on who in a market was overconfident and on how information in that market was disseminated.

The main assumptions of the empirical models were:

- a. Overconfidence was modeled as a belief that a trader's information was more precise than it actually was.
- b. How heavily information is weighted depended not only on overconfidence but also on the nature of the information. Psychologists find that when making judgments and decisions, people overweight salient information (Kahneman and Tversky (1973), Grether (1980)). As a result, people are prone to gather information that supports their beliefs, and readily dismiss information that does not (Lord, Ross and Lepper (1979), Nisbett and Ross (1980), Fiske and Taylor (1991)). In short, the overconfidence literature indicates that people believe their knowledge is more precise than it really is, they rate their own abilities too highly when compared to others, and they are excessively optimistic.
- c. In the models, traders updated their beliefs about the terminal value of

a risky asset on the basis of three sources of information: a private signal, their inferences from market price regarding the signals of others, and common prior beliefs. Consequently, and in consistence with the overconfidence literature, traders overweighed their private signals, they overweighed their own information relative to that of others, and they overestimated their expected utility.

- d. The main difference between the insider model and the price-takers model is that the insider model has noise traders and information is distributed in a different way. In the price-takers model, all traders received a signal, while in this model information is concentrated in the hands of a single insider. It is a one-period model in which a risk-neutral, privately informed trader (the insider) and irrational noise traders submit market orders to a risk neutral market maker.
- e. The market-makers model differs from the previous two models in the sense that the participants in this trading are the traders who buy the information (informed traders), traders who do not buy the information (uninformed traders) and noise traders who buy or sell without regard to price or value. Risk-averse traders decide whether or not to pay for costly information about the terminal value of the risky asset; those who buy information receive a common signal and a single round of trading takes place. All traders, even those who remain uninformed, are overconfident about the signal. In the previous models, traders were overconfident about their own signals but not those of others. Here, everyone believes the information is better than it is, but some decide the cost is still too high.

Odean then tested the following hypothesis in the three models:

Proposition 1: Does expected trading volume increase as overconfidence increases?

Proposition 2: Does overconfidence affect market efficiency?

Proposition 3: Does volatility of prices increase as overconfidence increases?

Proposition 4: Does overconfidence affect expected utility?

The results of Odean's study can be summarized as follows:

The effects of overconfidence were studied in three market settings that

differed mainly on how information was distributed and on how prices were determined. For some market measures, such as trading volume, overconfidence had a similar effect in each setting; i.e. overconfidence in the three types of traders increased expected trading volume. As a consequence, overconfidence increased market depth. When an insider was overconfident, he traded more aggressively for any given signal. The market maker adjusted for this additional trading by increasing market depth.

For other measures, such as market efficiency, the effect of overconfidence was not so clear. Whether overconfidence improves or worsens market efficiency depends on how information is distributed in the market. For example, when information was distributed in small amounts to many traders or when it was publicly disclosed and then interpreted differently by many traders, overconfidence caused the aggregate signal to be overweighed. This led to prices further from the asset's true value than would otherwise be the case. Though all information was revealed in such a market, it was not optimally incorporated into price. On the other hand, when information was held exclusively by an insider and then inferred by a market maker from order flow, overconfidence prompted the insider to reveal, through aggressive trading, more of his private information than he would otherwise would have, and therefore enabled the market maker to set prices closer to the asset's true value. Price-taking traders, who were overconfident about their ability to interpret publicly disclosed information, reduced market efficiency; overconfident insiders temporarily increased it. Nonetheless, overconfidence affected market efficiency.

In regards to volatility, traders' overconfidence increased volatility while market makers' overconfidence may have lowered it. However, in a market with many traders and few market makers it is unlikely that the decrease in volatility by overconfident market makers will offset increases in volatility due to overconfident trader.⁴ Overconfidence reduced the expected utility of overconfident traders, who did not properly optimize their expected utilities, which were therefore lower than if the traders were rational.

Finally, the impact of a private signal depends on how many people received that signal. The impact of traders, even rational traders, depended

on their numbers and on their willingness to trade. The mere presence of a few rational traders in a market did not guarantee that prices were efficient; rational traders may have been no more willing or able to act on their beliefs than biased traders. However, it was markets with higher proportions of rational traders that would be more efficient.

But how can these models be applied in practice? Odean believed that how each model is used depends on the characteristics of the market. For example, for a market in which crucial information is first obtained by well-capitalized insiders and market makers are primarily concerned about trading against informed traders, then the model of the overconfident insider is appropriate. However, if relevant information is usually publicly disclosed and then interpreted differently by a large number of traders each of whom has little market impact, the overconfident price-taker model applies. Finally, the market maker model would apply to markets in which traders choose between investing passively and expending resources on information and other costs of active trading.

Barber and Odean (1999) also believe that high levels of trading in financial markets are due to overconfidence. They sustain that overconfidence increases trading activity because it causes investors to be too certain about their own opinions and to not consider sufficiently the opinion of others. Overconfident investors also perceive their actions to be less risky than generally proves to be the case. In their paper, they test whether a particular class of investors, those with accounts at discount brokerages, trade excessively, in the sense that their trading profits are insufficient to cover their trading costs.

To test for overconfidence in the precision of information, their approach was to determine whether the securities bought by the investors outperformed those they sold by enough to cover the costs of trading. They examined return horizons of 4 months, one year and two years following each transaction (they calculated returns from the CRSP daily return files).

The results showed that not only did the securities these investors bought not outperform the securities they sold by enough to cover trading costs but, on average, the securities they bought underperformed those they sold.

The Importance of Illusion of Validity and Unrealistic Optimism

Psychologists Einhorn and Hogarth (1978) studied the general issue of why people persist in beliefs that are invalid, that is, why they succumb to the illusion of validity. They suggest that people do so because they are prone to search for confirming evidence, not disconfirming evidence (information that can be gained by the nonoccurrence of an action or prediction). Consequently, they not only may come to hold views that are fallacious, but they may be overconfident as well.

The question addressed in their article was: How can the contradiction between the evidence on the fallibility of human judgment be reconciled with the confidence people exhibit in their judgmental ability? In other words, why does the illusion of validity persist? And in trying to answer this question, the authors concentrated on the relationship between learning and experience; i.e. why does experience not teach people to doubt their fallible judgment? Their approach examined (i) the structure of judgmental tasks; (ii) the extent to which people could observe the outcomes of judgment; and (iii) how outcomes were coded and interpreted. The main results of their study were that:

- It is extremely difficult to learn from disconfirming information. As a result, people failed to seek disconfirming evidence and relied on positive instances to make judgments of contingency.
- Outcomes appeared to be coded as frequencies rather than probabilities (probability differs from frequency in that frequency is divided by all elementary events in the sample space (assuming that all events have the same probability of occurrence)). Experimental evidence showed that the way in which predictions and subjective probability judgments were made on the basis of the coded outcomes suggested that frequency was more salient in memory than probability.
- The difficulty in learning from experience was traced to three main factors: (a) lack of search for and use of disconfirming evidence; (b) lack of awareness of environmental effects on outcomes; and (c) the use of unaided memory for coding, storing, and retrieving outcome information.

Consequently, not only they may come to hold views that are fallacious, but they may be overconfident as well.

Furthermore, people are also found to be unrealistically optimistic about future life events. Weinstein (1980) focused on two studies that investigated the tendency of people to be unrealistically optimistic about future life events. The two studies tested the following hypotheses:

- a. People believe that negative events are less likely to happen to them than to others, and they believe that positive events are more likely to happen to them than to others.
- b. Among negative events, the more undesirable the event, the stronger the tendency to believe that one's own chances are less than average; among positive events, the more desirable the event, the stronger the tendency to believe that one's own chances are greater than average.
- c. The greater the perceived probability of an event, the stronger the tendency for people to believe that their own chances are greater than average.
- d. Previous personal experience with an event increases the likelihood that people will believe their own chances are greater than average (i.e. past personal experience influences people's beliefs about their chances of experiencing an event).
- e. People often bring to mind actions that facilitate rather than impede goal achievement.

Study 1 was designed to test the hypotheses themselves. Its goal was to determine the amount of unrealistic optimism associated with different events and to relate this optimism to the characteristics of the events. In Study 1, 258 college students estimated how much their own chances of experiencing 42 events differed from the chances of their classmates. The results of the study supported all hypotheses. In particular, the study showed that they rated their own chances to be above average for positive events and below average for negative events. It also concluded that the degree of desirability, the perceived probability, personal experiences, perceived controllability and stereotype salience influenced the amount of optimistic bias evoked by different events.

Study 2 tested the idea that people are unrealistically optimistic because they focus on factors that improve their own chances of achieving desirable

outcomes and fail to realize that others may have just as many factors in their favor. Subjects in Study 2 made written lists of the factors that increased or decreased the likelihood that specific events would happen to them. Some subjects were then given copies of the lists generated by others and asked to make comparative judgments of their chances of experiencing these events. It was predicted that exposure to others' lists would decrease their optimistic biases.

The results of the study suggested that optimistic biases arose because people tended not to think carefully about their own and others' circumstances or because they lacked significant information about others. However, the study showed that there were more persistent sources of optimism that could not be eliminated just by encouraging people to think more clearly about their comparative judgments or by providing them with information about others (providing information about the attributes and actions of others reduced the optimistic bias but did not eliminate it). In short, these studies were successful in demonstrating the existence of an optimistic bias concerning many future life events.

How can investment decisions be affected by overconfidence?

For Daniel and Titman (1999) overconfidence has both a direct and an indirect effect on how individuals process information. The direct effect, discussed by Daniel, Hirshleifer and Subrahmanyam (1998) is that individuals place too much weight on information they collect themselves because they tend to overestimate the precision of that information. The indirect effect arises because individuals filter information and bias their behavior in ways that allow them to maintain their confidence (people tend to ignore or underweight information that lowers their self-esteem).

The authors also believe that overconfidence does not bias the pricing of all securities equally. Experimental evidence suggests that overconfidence is likely to influence the judgment of investors relatively more when they are analyzing a security with vague, subjective information. Moreover, their analysis suggests that investor overconfidence can generate momentum in

stock returns and that this momentum effect is likely to be stronger in those stocks whose valuations require the interpretation of ambiguous information.

Consistent with this hypothesis, the results of their study found that momentum effects were stronger for growth stocks than for stable stocks. Additionally, a portfolio strategy based on this hypothesis generated strong abnormal returns from US equity portfolios that did not appear to be attributable to risk.

The main implication of this study is that investment decisions are, in fact, affected by overconfidence, and that the traditional efficient market hypothesis may be violated.

3) Strength and weakness analysis: Were the research methods appropriate to measure overconfidence? What questions have been left unanswered?

In conclusion, when people are overconfident, they tend to overestimate the precision of their knowledge and their ability to do well on tasks, they are unrealistically optimistic about future events, and they see themselves as better than the average person.

Several authors have successfully defined overconfidence and have shown how financial markets can be affected by this behavioral factor. The research designs used to identify the factor were appropriate, but as usual, assumptions can be questioned. However, the assumptions discussed above are valid and necessary in order to model behavior. Nonetheless, several questions arose from this analysis, mainly (a) How can overconfidence be incorporated in a valuation model? and (b) Do investment strategies based on overconfidence deliver abnormal returns?

Fuller and Thaler Asset Management (F&T) offers an example of trading on a behavioral bias: the fund believes that both analysts and investors are slow to recognize the information associated with a major earnings surprise. Instead, they overconfidently remain anchored to their prior view of the company's prospects. That is, they underweight evidence that disconfirms their prior views and overweight confirming evidence. Consequently, both analysts and investors interpret a permanent change as if it were temporary; thus, the price is slow to adjust. F&T strategy consists in buying a stock soon

after a major positive earnings surprise and holding it until the positive earnings surprises diminish or disappear. However, the returns of this strategy have varied through time.

The fund’s strategies range from micro-cap to large-cap and they include U.S., international and global equity strategies. For example, domestic U.S. strategies include Micro-Cap, Small/Mid-Cap Core, Small/Mid-Cap Growth and Small/Mid-Cap Value. Their performances were as follows:

Chart 1. Annualized Returns					
	1Q2007	1 Year	3 Year	5 Year	Since Inception
Micro-Cap(Net)	-0.90%	-8.60%	6.40%	15.20%	25.70%
Russell 2000 / Russell Microcap ⁺	0.90%	3.10%	11.60%	10.70%	9.30%
The Russell 2000 was the benchmark from 1/1/1999 through 6/30/2005 and the Russell Microcap thereafter. Returns are net-of-fees estimates as of March 31, 2007 and are annualized except for Last Quarter Index returns are gross-of fees. Source: Fuller and Thaler (2007:3).					

	1Q2007	1 Year	3 Year	5 Year	10 Year	Since Inception
Small/Mid-Cap Core (Net)	4.20%	5.40%	11.10%	13.10%	14.50%	15.00%
Russell 2500	3.60%	8.20%	13.30%	12.10%	12.00%	12.00%
Small/Mid-Cap Growth (Net)	5.20%	0.40%	8.10%	11.10%	12.00%	15.40%
Russell 2500 Growth	4.00%	4.40%	11.10%	9.10%	8.40%	9.00%
Small/Mid-Cap Value (Net)	3.40%	9.00%	12.50%	14.50%	17.20%	17.40%
Russell 2000 Value	1.50%	10.40%	14.50%	13.60%	13.50%	13.80%
Returns are net-of-fees estimates as of March 31, 2007 and are annualized except for Last Quarter Index returns are gross-of fees. Source: Fuller and Thaler (2007:3).						

These results show that the strategies have difficulty in beating the benchmarks in the short term but have better results in the medium and long term. However, since inception, all strategies have beaten the benchmark and have been profitable.

Daniel and Titman (1999) also developed a portfolio strategy based on the hypothesis that overconfidence affects difficult to value companies more than stable companies. But how could they determine the vagueness versus concreteness of the information used in performing valuation? One measure of this characteristic was the fraction of a company's value that was in growth options, which could be obtained from a company's book to market value (B/M). As a result, their hypothesis was as follows: to the extent that lower B/M companies have more growth options, the prices of their stocks should exhibit stronger overconfidence effects, and momentum effects should be stronger for hard to value growth stocks than for stable stocks.

To test this hypothesis, the authors analyzed the performance of 125 portfolios sorted by size, book to market value (B/M), and momentum. To form these portfolios, they grouped the universe of listed common stocks from the NYSE, Amex, and Nasdaq, into 3 quintile groupings based on market capitalization, B/M, and prior year's return. Then they formed 25 portfolios by equally weighting the 5 corresponding size-sorted portfolios. Then they calculated the monthly average returns for these 15 portfolios between July 1963 and December 1997. Consistent with the predictions of the overconfidence model, the momentum effect was much stronger for low B/M stocks.

In a second phase, they analyzed the monthly average returns for similar portfolios that excluded the largest-cap and smallest-cap quintile (the largest-cap stocks were presumably the most efficiently priced, so any behavioral effects should be more apparent when these stocks were removed from the sample, while the smallest-cap stocks had the least reliable prices). They then compared the returns of various B/M-momentum portfolios to the return of the CRSP value weighted index (which closely tracks the S&P500). The results showed that the high B/M-momentum portfolio in the study period outperformed the value-weighted index and that low B/M-low momentum portfolios underperformed the value-weighted index by a similar amount.

Finally, they studied the performance of long-short strategies for 1964-1997 that bought the high B/M-high momentum portfolio and sold the low B/M-low momentum portfolio for all quintiles and then for quintile 2-4. The performance of these portfolios was striking. The all-quintile strategy realized an average annual return of 12.4% a year, generating profits in 31 out of 34 years in the sample period.

The main conclusion is that the evidence rejects the notion of efficient markets in favor of an alternative theory in which asset prices are influenced by investor overconfidence. The previous studies show that portfolio strategies that may be suggested by the overconfidence theory can realize high abnormal returns (which cannot be explained by additional risk). However, are these trading strategies more profitable than other trading strategies? Are they persistently successful? How would these strategies perform in another sample period or in another market? Is it worth introducing overconfidence into the models?

Overreaction

1) Identification of its main issues and propositions.

Research in experimental psychology suggests that, in violation of Bayes' rule, most people tend to overreact to unexpected and dramatic news events, overweighting recent information and underweighting prior data (De Bondt and Thaler, 1985). Shefrin (1998) relates this concept to *representativeness*, which he identifies as 'one of the most important principles affecting financial decisions, and it refers to judgments based on stereotypes'.

But how does this behavior affect stock prices? Shefrin believes that 'investors who rely on the representativeness heuristic become overly pessimistic about past losers and overly optimistic about past winners, and this instance of heuristic-driven bias causes prices to deviate from fundamental value'.

Specifically, investors overreact to both bad and good news. Therefore, overreaction leads past losers to become underpriced and past winners to become overpriced. However, empirical research shows that this mispricing

is not permanent; over time the mispricing corrects itself. The losers will outperform the general market, while winners will underperform.

2) *Empirical models: research designs and methodology.*

Several research papers have focused on overreaction, but perhaps the most notorious financial example illustrating representativeness and overreaction is the winner-loser effect documented by De Bondt and Thaler (1985, 1987).

In their 1985 study, De Bondt and Thaler carried out an empirical test of the overreaction hypothesis, trying to identify if the overreaction hypothesis was predictive; i.e. whether it did more than merely explain, ex post, the results on asset price dispersion. Their two hypotheses were as follows: (a) extreme movements in stock prices will be followed by subsequent price movements in the opposite direction; and (b) the more extreme the initial price movement, the greater will be the subsequent adjustment. It is important to notice that both hypotheses imply a violation of weak-market efficiency.

The basic research design used to form the winner and loser portfolios was as follows:

- Monthly return data for New York Stock Exchange (NYSE) common stocks for the period between January 1926 and December 1982 were used (compiled by the Center for Research in Security Prices (CRSP) of the University of Chicago). An equally weighted arithmetic average return on all CRSP listed securities served as the market index.
- For every stock j with at least 85 months of return data, monthly residual returns were estimated μ_{jt} . The procedure was repeated 16 times starting in January 1930, January 1933, ..., up to January 1975.
- For every stock j , starting in December 1932, they computed the cumulative excess returns (CU_j) for the prior 36 months. This step was repeated 16 times for all non-overlapping three-year periods between January 1930 and December 1977.
- On each of the relevant portfolio formation dates (Dec. 1932, Dec. 1935, etc), the CU_j 's were ranked from low to high and portfolios were formed. Firms on the top decile were assigned to the winner portfolio W ; firms in the bottom decile to the loser portfolio L . In other words, the authors

formed portfolios of the most extreme winners and of the most extreme losers, as measured by cumulative excess returns over successive three year formation periods.

Consistent with the predictions of the overreaction hypothesis, portfolios of prior losers were found to outperform prior winners: loser portfolios of 35 stocks outperformed the market by, on average, 19.6%, 36 months after portfolio formation; meanwhile, winner portfolios earned about 5% less than the market, so that the difference in cumulative average residual between the extreme portfolios equaled 24.6% (t statistic: 2.20). In other words, thirty-six months after portfolio formation, the losing stocks earned about 25% more than the winners, even though the survey showed that the latter were significantly more risky (the average betas of the securities in the winner portfolios were significantly larger than the betas of the loser portfolio). Additionally, the tests showed that: (i) the overreaction effect was asymmetric; it was much larger for losers than for winners (it was reported that after the date of portfolio formation, losers won approximately three times the amount that winners lost); (ii) stocks that went through more (less) extreme return experiences showed subsequent price reversals more (less) pronounced; and (iii) a strong seasonality was present as a large portion of the excess returns occurred in January.

The interpretation of the results as evidence of investor overreaction was questioned by Vermaelen and Verstringe (1986), who claim that ‘the overreaction effect is a rational market response to risk changes’. Their risk-change hypothesis states that a decline (increase) in stock prices leads to an increase (decline) in debt-equity ratios and in risk as measured by CAPM betas.⁵

Using the same data set as in their 1985 paper, De Bondt and Thaler wrote a follow-up paper in 1987 where they address the issues of seasonality and firm size. While trying to explain the seasonality patterns present in the results of the 1985 paper, the authors pose the following questions: (i) Were there any seasonal patterns in returns during the formation period?; (ii) Were the January corrections driven by recent share price movements (say, over the last few months), or by more long-term factors?; and (iii) Could the winner-loser effect be explained by changes in CAPM betas?

The basic research design used to form the winner and loser portfolios was as follows:

- For every stock j on the CRSP monthly return data (1926-1982) with at least 61 months of return data, and starting in January 1926, they estimated 120 monthly market-adjusted excess returns, $\mu_{jt} = R_{jt} - R_{mt}$, covering both a five-year portfolio “formation” and a five-year “test” period. The procedure was repeated 48 times for each of the ten-year periods starting in January 1926, January 1927, and up to January 1973.
- For every stock in each sample, they computed the cumulative excess returns (CU_j) over the five-year formation period. After that, the CU_j 's were ranked from low to high and portfolios were formed. The 50 stocks with the highest CU_j 's were assigned to the winner portfolio W ; the 50 stocks with the lowest CU_j 's to the loser portfolio L . In total there were 48 winner and 48 loser portfolios, each containing 50 securities.
- For the five sequences of all non-overlapping formation periods that start in January 1926, January 1927, and up to January 1930, the single most extreme winners from each formation period were combined to form group W_1 . The stocks that came in second in the formation period formed group W_2 , etc. Consequently, they had, for each of the five experiments, 50 “rank portfolios” for winners, W_1, \dots, W_{50} , and 50 “rank portfolios” for losers formed in the same way. In total there were 250 winner and 250 loser rank portfolios. Finally, average and cumulative average excess returns were found for each rank portfolio.

The authors confirmed that seasonality was present in both the test period returns and the formation period returns. During the test period, losers earned virtually all of their excess returns in January, while winner excess returns (though smaller in absolute terms than for losers), also occurred predominantly in January. In the formation period, the January excess returns for winners were about double that of the abnormal performance in other months. For losers, the seasonal pattern was also present.

These results raised the question of to what extent the January returns of long-term winners and losers were actually driven by performance over the immediately preceding months, possibly reflecting tax-motivated trading.

The authors found that excess returns for losers in the test period (and particularly in January) were negatively related to both long-term and short-term formation period performance. For winners, January excess returns were negatively related to the excess returns for the prior December, possibly reflecting a capital gains tax “lock-in”. Additional tests and findings continued to be consistent with tax explanations of the unusual January returns.

Regarding their last question, in their previous paper, the authors had found out that regardless of the length of the formation period, the beta for the loser portfolio was always lower than the beta for the winner portfolio. However, Chan (1986) and Vermaelen and Verstringe (1986) argued that the usual procedure of estimating betas over a prior period was inappropriate if betas varied with changes in market value. For winners and losers, a negative correlation between risk and market value is plausible because of changes in financial leverage that accompany extreme movements of the value of equity. The implication is that the winner-loser effect may disappear if the risk estimates were obtained during the test period. They argued that De Bondt and Thaler should have looked at the test period betas, as risk may have changed as the losers were losing and the winners were winning. Still, the test period betas were only slightly higher for losers than for winners (1.263 vs 1.043) and this estimated risk difference was not capable of explaining the gap in returns. In other words, the winner-loser effect could not be attributed to changes in risk as measured by CAPM betas.

In regards to the size effect, De Bondt and Thaler (1987) also tried to identify if the winner-loser effect was qualitatively different from the size effect. In particular, they tried to answer two questions: (i) are losing firms particularly small?; and (ii) are small firms (size measured by market value of equity) for the most part losers? The basic research design used was as follows:

- The sample included both NYSE and AMEX firms listed in COMPUSTAT for the years 1966-1983.
- For each firm j , annual returns R_{jt} and excess returns μ_{jt} were computed from COMPUSTAT data for all years between $t-3$ and $t+4$, with t representing the final year of the formation period.

- Every sample was ordered by each of the following 4 rankings: (a) cumulative excess return (CU_j) over a four-year formation period between the end of year $t-4$ and the end of year t ; (b) market value of equity (MV) at the end of year t ; (c) market value of equity divided by book value of equity (MV/BV); (d) company assets at t .
- For each sample and for each ranking variable, quintile, decile and ventile portfolios were formed. Average and cumulative average excess returns were calculated for the four years between $t-3$ and t , and for the four years between $t+1$ and $t+4$.

The results showed that even for quintile portfolios, (which are less extreme than the decile or groups of 50 stocks used in their previous study) the losers had positive excess returns and the winners had negative excess returns. However, they were not able to describe the winner-loser anomaly as primarily a small firm phenomenon. On the other hand, they were able to show that the size effect, as measured by MV, was partly a losing effect; i.e. there was a relationship between the size effect and the losing firm effect. The firms in the loser portfolios had lost a substantial portion of their value. Since the firm size is usually measured by the MV of equity, the losing firms became much smaller during the formation period.

In short, the results showed that (i) the winner-loser effect is not primarily a size effect; (ii) the small firm effect is partly a losing firm effect, but even if the losing firm effect is removed by using a more permanent measure of size, such as assets, there are still excess returns to small firms; and (iii) the earnings of winning and losing firms showed reversal patterns that were consistent with overreaction.

Following the results from their 1987 paper, De Bondt and Thaler (1989) referred to the concept of mean reversion.⁶ The idea that systematic “irrationality” in investors’ attitudes may affect prices, and that prices may deviate from fundamental value, raised the following question: do stock prices follow a random walk or are they somewhat predictable?

The efficient market view claims that stock prices quickly and rationally reflect all public information; i.e. stock prices follow a stochastic process close to a random walk. On the other hand, the overreaction hypothesis admits to

temporary disparities between prices and fundamentals. So De Bondt and Thaler tried to show that if overreaction was present in financial markets, then we should observe mean-reverting returns to stocks that have experienced extremely good or bad returns over the past few years. Referring to the 1985 paper, they showed that (i) the returns for both winners and losers were mean-reverting; and (ii) the five-year price reversal for losers was more pronounced than for winners. In addition, and consistent with overreaction, they showed that the more extreme the initial price movements, the greater the subsequent reversals. Additionally, they tested mean reversion in the short term. If mean reversion was observed over very brief time periods, factors other than size or objective risk could be assumed to be at work.⁷ Basing their analysis on the study carried out by Bremer and Sweeny (1988), they showed that there was a significant correction for losers in the short term, but not for winners, and that the correction increased with the size of the initial price jump.

Several conclusions follow from these results⁸ but the main one is that although prices may deviate from fundamental value, eventually, they get corrected as actual future events predictably turn out to be more or less than expected. A consequence for portfolio management is that this price behavior explains the profitability of contrarian strategies. Contrary to market efficiency, prior stock market “losers” are much better investments than prior “winners”.⁹

In a later work, De Bondt and Thaler (1990) present a study of the expectations of security analysts who make periodic forecasts of individual company earnings. They specifically test for a type of generalized overreaction, the tendency to make forecasts that are too extreme, given the predictive value of the information available to the forecaster. Their focus is on forecasted changes in earnings per share (EPS) for one and two year time horizons. In particular, they tried to answer the following questions: Are forecast errors in EPS systematically linked to forecasted changes? Are the forecasts too extreme (so actual changes are less than predicted)? Are most forecast revisions “up” (“down”) if the analysts’ initially projected large declines (rises) in EPS? (Under rationality, neither forecast errors nor forecast revisions should ever be predictable from forecasted changes). Does the bias in the forecasts get stronger as uncertainty grows and less is known about the future?

In order to answer these questions, they used the following research design:

The analysts' earnings forecasts between 1976 and 1984 were taken from the Institutional Brokers Estimate System tapes (IBES) produced by Lynch, Jones & Ryan. They worked only with the April and December predictions of EPS for the current as well as the subsequent year. They matched the earnings forecasts for each company with stock returns and accounting numbers as provided by the CRSP at the University of Chicago and the annual industrial COMPUSTAT files. Most of the regression analysis was based on three sets of variables: forecasted changes in EPS, actual changes in EPS, and forecast revisions.

The results of the study showed that forecasts were too optimistic, too extreme, and even more extreme for two-year forecasts than for single-year predictions. They also showed that forecast revisions were predictable from forecasted changes, violating the rationality assumption. In sum, the results were consistent with generalized overreaction.

The authors' main conclusion is that even the predictions of security analysts, who may be considered a source of rationality in financial markets, present the same pattern of overreaction found in the predictions of naïve undergraduates. Forecasted changes are simply too extreme to be considered rational.

Along the same lines, De Bondt (1991) continued to analyze regression to the mean in the belief that strategists are prone to committing gambler's fallacy, a phenomenon where people inappropriately predict reversal. Gambler's fallacy is regression to the mean gone overboard (overreaction). His survey examined the market prediction collected by Joseph Livingston since 1952.¹⁰ In particular, he examined about 5400 individual forecasts of the S&P index and of 425 industrial companies for the period between 1952 and 1986. The time horizon was seven and thirteen months.

In accordance with gambler's fallacy, De Bondt found that these predictions consistently were overly pessimistic after a bull market and overly optimistic after a bear market. In particular, the results showed that, after three-year bull markets, economist predicted that on average, over the next seven

months, the S&P would decline at an annual rate of 6.4%. He concluded that this pessimism was not borne out by the facts even though actual returns turned out to be much smaller after large price run-ups than after market declines. Actual returns were less than expected returns if the market was expected to rise and more than expected if a decline was predicted.

The results also showed that professional economists expected reversals in stock prices. After three-year bull markets, on average, 52.6% of the subjects saw a weak downward trend. The equivalent number for three-year bear markets was only 17.8%. But a curious finding is that these results on mean reversion in stock prices were unknown to the survey participants; i.e. they did not know that the average economist is a contrarian, pessimistic in bull markets and optimistic in bear markets.

De Bondt continued by asking the following question: What does regression to the mean suggest about predictions in the wake of above-average performance? He concluded that it implies that future performance will be closer to the mean, not that it will be below the mean in order to satisfy the law of averages.

Up to this point, academic research provided us with evidence of medium to long term reversals. Lehman (1990) argues that shorter-term reversals can also be observed.¹¹ Lehman believes that predictable variations in equity returns may reflect either predictable changes in expected returns or market inefficiency and stock price overreaction. He believes that these explanations can be distinguished by examining returns over short time intervals since systematic changes in fundamental valuation over intervals like a week should not occur in efficient markets. He argues that 'asset prices should follow a martingale process over short time intervals even if there are predictable variations in expected security returns over longer horizons –systematic short-run changes in fundamental values should be negligible in an efficient market with unpredictable information arrival'. As a consequence, rejection of this martingale behavior over short horizons would be evidence against market efficiency.

Lehman tested the market efficiency hypothesis by examining security prices for evidence of unexploited arbitrage opportunities. His model was

based on the assumption that any stock price overreaction infects many securities returns. Consequently, well-diversified portfolios composed of either “winners” or “losers” might be expected to experience return reversals in these circumstance. As a result, he developed a simple strategy to test market efficiency: he studied the profits of costless (i.e. zero net investment) portfolios which gave negative weight to recent winners and positive weight to recent losers. The short run martingale model predicted that these costless portfolios should earn zero profits. In contrast, if stock prices did overreact, violating the efficient market hypothesis, these costless portfolios would typically profit from return reversals over some horizon.

The research design implemented was as follows: Equity securities listed on the New York and American Stock Exchange were used from 1962 to 1986. Portfolio weights were taken to be proportional to the difference between the return of security i and the return on an equally weighted portfolio at different lags; i.e. the number of dollars invested in each security was proportional to the return in week k less the return of the equally weighted portfolio. A week was considered to be a sufficiently short period for the martingale model to apply under the efficient market hypothesis; i.e. weekly security returns were used. Profits were reported for five horizons: one, four, thirteen, twenty six and fifty two weeks.

The results of this study strongly suggest rejection of the efficient market hypothesis. His results showed that the “winners” and “losers” one week experienced sizeable return reversals the next week in a way that reflected arbitrage profits. In other words, portfolio of securities that had positive returns in one week typically had negative returns in the next week, while those with negative returns in one week typically had positive returns in the next week. The costless portfolio that is the difference between the winners and losers portfolios had positive profits in 90% of the weeks.

However, the results failed to find pronounced persistence in the return reversal effect. On average, the winner portfolio only had negative mean returns in the subsequent week but had positive and increasing mean returns over the next month. Similarly, the loser portfolio had large positive mean returns in the subsequent week but they diminished over the next month.

3) *Strength and weakness analysis: Were the research methods appropriate to measure overreaction? What questions have been left unanswered?*

In conclusion, the overreaction hypothesis believes that, in violation of Bayes' rule, most people tend to overreact to unexpected and dramatic news events, overweighting recent information and underweighting prior data. The winner-loser effect documented by De Bondt and Thaler is, perhaps, the most illustrative example of overreaction. Their work, as well as the research that followed, is successful in proving that investors overreact. The research designs were appropriate and the questions that arose as a result of one publication was answered in following papers, either by the same authors or by other researchers.

However, the empirical analysis showed some limitations and several questions have not yet been answered. These issues can be grouped into four broad considerations:

First: Can overreaction explain the behavior in stock prices and returns? De Bondt and Thaler (1985) argue that mean reversion is evidence of overreaction. They showed that over the 3 to 5-year holding period, stocks that performed poorly over the previous 3 to 5 years achieve higher returns than stocks that performed well over the same period. In the 1987 paper they showed that these excess returns could not be easily attributed to changes in risk or the "small firm anomaly".¹² However, as stated by Jegadeesh and Titman (1993), De Bondt and Thaler's results are still being debated.

In De Bondt and Thaler (1985), the winner and loser portfolios were formed conditional upon past excess returns, rather than some firm-generated informational variable such as earnings. But can past returns be considered good predictors of future returns? Additionally, the requirement that 85 subsequent returns were available before any firm was allowed in the sample biased the selection towards large, established firms. Consequently, can these results be generalized?

De Bondt and Thaler also showed that 36 months after portfolio formation, the losing stocks earned about 25% more than the winners, even though the survey showed that the latter were significantly more risky (the average betas

of the securities in the winner portfolios were significantly larger than the betas of the securities in the loser portfolio). The authors identified this issue but failed to explain why this happened. In other words, is it correct to assume that the risk-return relationship implicit in the efficient markets hypothesis was violated? And what can be implied by these results? However, in trying to solve this issue and also answer the question raised by Chan (1986) and Vermaelen and Verstringe (1986) that the winner-loser effect may disappear if the risk estimates were obtained during the test period, their 1987 paper found that the test period betas were only slightly higher for losers than for winners and that this estimated risk difference was not capable of explaining the gap in returns. In other words, they showed that if the CAPM beta is an adequate risk measure, then the difference between the winner and the loser returns could not be attributed to differences in risk.

Some final comments refer to asymmetric overreaction and seasonality. The authors identified that the overreaction effect was asymmetric, but they failed to explain why. Additionally, although the authors offered an explanation of the strong seasonality present in their results, significant research had to follow in order to explain this phenomenon.

Second: Is mean reversion a sign of market inefficiency? And are contrarian strategies the answer? The fact that prices are mean reverting implies that prices are predictable. But as stated by Fama and French (1986), does predictability reflect market inefficiency or time-varying expected returns generated by rational investor behavior? Mean reversion can also explain the profitability of contrarian strategies. In particular, Lehman's results (1990) showed that the "winners" and "losers" one week experienced sizeable return reversals the next week in a way that reflected arbitrage profits. In particular, relative strength strategies that bought past winners and sold past losers have been documented to show significant abnormal returns¹³ (practitioners in USA still use this strategy as one of their stock selection criteria (Grinblatt and Titman, 1989, 1993). These results strongly suggested rejection of the efficient market hypothesis. But do these contrarian strategies offer consistent abnormal returns over other strategies? Is it profitable always to invest using contrarian strategies?

Moreover, the evidence on short-term reversals presented by Jegadeesh (1990) and Lehmann (1990) can also be criticized. These papers show that contrarian strategies that select stocks based on their returns in the previous week or month generate significant abnormal returns. However, since these strategies are based on short-term price movements, their apparent success may reflect the presence of short-term price pressure or a lack of liquidity in the market rather than overreaction.¹⁴ Additionally, the explanation of why there is little persistence in the return reversal effects is not sufficient. Lehman offers two possible explanations: ‘first, one could emphasize the short-run nature of the arbitrage opportunity and presume that equity markets are (on average) efficient over longer horizons...alternatively, one could emphasize the low power of the tests for detecting longer term market inefficiencies and continue to seek additional evidence (and reinterpret existing evidence) of market inefficiency’. However, further analysis is needed to address this issue in full.

Third: What causes the overreaction phenomenon; in other words, what causes the systematic excessive optimism or pessimism present in forecasters? De Bondt and Thaler (1990) showed that EPS forecasts were too optimistic and too extreme. However and even though they tried to explain the EPS forecast error, they failed to identify the causes of this excessive optimism or pessimism in earnings forecasts. This same question was also present in De Bondt’s 1991 survey. The author offered some explanations, focusing on expected inflation, expected real economic growth, the S&P price-earnings ratio on the forecast date, and the three-year cumulative historical returns immediately prior to the forecast. Another explanation of this behavior has been offered by Shefrin (1998): Regret and hindsight bias come together in the selection of loser stocks for a portfolio: people are fearful of investing in loser stocks, although evidence has shown that a portfolio of losers historically outperformed the market. But these explanations are not satisfactory; further research is necessary.

Fourth: How does the overreaction hypothesis affect portfolio theory and portfolio selection; i.e. how can these anomalies be incorporated into existing models? The proponents of market efficiency hold that there are

enough well-informed investors to seize all unexploited profit opportunities. The evidence from behavioral decision-making studies is that people learn slowly. So, are there enough quick learners to eliminate mispricing in financial markets? DeBondt and Thaler believe that because of representativeness, investors become overly optimistic about recent winners and overly pessimistic about recent losers. Hence, they propose buying past losers and selling past winners. If prices either overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist, achieving abnormal returns.

However, strategies based on relative strength have also been proven to show abnormal returns.¹⁵ In 1993 Jegadeesh and Titman documented the strategies that bought stocks that had performed well in the past and sold stocks that had performed poorly in the past. In other words, the authors tested the inverse trading strategy proposed by DeBondt and Thaler in 1985. In particular, Jegadeesh and Titman (1993) provided an analysis of relative strength trading strategies over 3 to 12 month horizons (in each month t , the strategy bought the winner portfolio and sold the loser portfolio). Their results showed that: (i) trading strategies that bought past winners and sold past losers realized significant abnormal returns over the 1965 to 1989 period; (ii) the profitability of the relative strength strategies was not due to their systematic risk; (iii) profits could not be attributed to a lead-lag effect resulting from delayed stock price reactions to information about a common factor, although the evidence was consistent with delayed price reactions to firm-specific information; (iv) part of the predictable price changes that occurred during the 3 to 12 month holding periods may not have been permanent (the longer-term performances of the past winners and losers revealed that half of their excess returns in the year following the portfolio formation date dissipated within the next 2 years).

So, which trading strategy is more profitable? Can they be compared? Jegadeesh and Titman (1993) offered an explanation: the discrepancy between the results of both trading results may be due to the difference between the time horizons used in the trading rules examined in the academic papers and those used in practice. For example, they cited evidence favoring contrarian

strategies focusing on trading strategies based on either very short-term return reversals (1 week or 1 month), or very long-term return reversals (3 to 5 years). However, evidence suggested that practitioners who use relative strength rules base their selection on price movements over the past 3 to 12 months.¹⁶

Another alternative that has been proposed is the study of the excess returns from value investing. Graham and Dodd (1934) found that excess returns were obtainable from a low P/E strategy. The results showed that buying stocks with low P/E led to excess risk-adjusted returns, and the extreme losers outperformed the market. This strategy was replicated in the United States and Japan, showing similar results.¹⁷

Taking all this into account, is it worth incorporating these anomalies into existing models? I believe it is but further research that attempts to identify explanations for these empirical irregularities is necessary. As De Bondt and Thaler (1989) state, 'the real challenge facing the field (of finance) is to develop new theories of asset pricing that are consistent with known empirical facts and offer new testable predictions'. The authors suggest models in which some agents have non-rational expectations of future cash flows, or have faulty risk perceptions (versus traditional models in which all agents are assumed to be fully rational).

IV. Implications of overconfidence and overreaction for market efficiency and investors' rational behavior and the responses given by the Traditional Finance Theory

In the above discussion, it was implied that the presence of overconfidence and overreaction in investors' choices affects the efficient market hypothesis and may cause prices to deviate from fundamental value. However, Traditional Finance Theory has addressed some of these issues and several responses have been given. As a result, the objective of this section is to analyze the implications of the anomalies regarding overreaction and overconfidence for market efficiency, rational behavior and fundamental value, and to analyze the responses given by the Traditional Finance Theory.

Let's recall that the traditional theory of finance assumes that individuals are rational; i.e. they develop expectations using Bayesian strategies and make optimal decisions based on the available information. As a result, prices reflect all available information, so opportunities to earn extraordinary returns arise only from new information. Since the arrival of unexpected information is random, prices will follow a random walk and returns will be normally distributed (i.e., the entire return distribution can be described by its mean and its standard deviation).

As Fama (1970) explains, on the one hand, it is easy to determine sufficient conditions for capital market efficiency, such as: (i) the lack of transaction costs in trading securities; (ii) all available information is costlessly available to all market participants; and (iii) all agree on the implications of current information for the current price and distributions of future prices of each security. In this world, Fama sustains that it is easy to assume that the current price of a security fully reflects all available information.

However, a market with these conditions is not met in practice. As a result, numerous studies have tested the efficient market hypothesis throughout the years. Testing market efficiency is basically straightforward: using statistical methods, investigate whether a strategy (based on a certain kind of information) consistently earns abnormal profits. Some examples included: (1) tests of technical trading rules; (2) earnings, dividends and split announcements; (3) trading performance of insiders (results from trading on public information about insider trades) (Daniel, 2002).

As Fama (1970) explains, the initial studies were concerned with "weak form" tests in which the information set was just historical prices. In the early literature, discussions of the efficient markets model were phrased in terms of the random walk model. The impetus for the development of a theory came from the accumulation of evidence in the middle 1950's and early 1960's that the behavior of common stock and other speculative prices could be well approximated by a random walk. Faced with the evidence, economists offered some rationalization, which resulted in a theory of efficient markets stated in terms of random walks.

When the tests seemed to support the efficiency hypothesis at this level,

attention was turned to “semi strong form” tests in which the concern was whether current prices “fully reflected” all obviously publicly available information. Each individual test, however, was concerned with the adjustment of security prices to one kind of information generating event (e.g. stock splits, announcements of financial reports by firms, new security issues, etc.).

By the time Fama wrote his 1970 paper, “strong form” tests had begun to appear. The strong form tests of the efficient markets model were concerned with whether all available information was fully reflected in prices in the sense that no individual had higher expected trading profits than others because he had monopolistic access to some information.

Lehmann (1990) also referred to this issue and explained that testing of the efficient market hypothesis was abundant. Earlier studies supported the random walk model, finding that the predictable variation in equity returns was both economically and statistically small. More recently, however, several studies began to document other examples of how market efficiency could be violated. For example, as Fama (1991) explains, a precondition for the strong version of the efficient market hypothesis is that information and trading costs, the costs of getting prices to reflect information, are always 0. Since there are surely positive information and trading costs, the extreme version of the market efficiency hypothesis is surely false.

Additionally, recent research has found evidence that equity returns can be predicted with some reliability. In other words, there is evidence on the predictability of daily and weekly returns from past returns.

As Raghurir and Ranjan Das (1999) state, the findings of persistent deviation of stock prices from fundamentals are robust, suggesting that the behavioral cause behind these price deviations is overreaction, which implies that stock prices do not display a random walk but rather display return predictability (Shiller, 1981, and Shleifer and Vishny, 1990).

Lehman argues that there are two competing explanations for this phenomenon. The first is that the returns vary through time, resulting in predictable, but efficient, mean reversion in stock prices. On the other hand, the predictability of equity returns may reflect the overreaction of stock

prices, as suggested by De Bondt and Thaler. But these two explanations can be distinguished by examining asset returns over short time intervals. As explained in the previous section, Lehman tested this hypothesis and the results showed that the “winners” and “losers” one week experienced sizeable return reversals the next week in a way that reflected arbitrage profits. The results of this study strongly suggest rejection of the efficient market hypothesis. Additionally, Shiller (1979) argues that there is more volatility in stock markets and bond markets than would be the case if prices were determined by fundamental value alone.

In other words, the evidence of systematic reversals in stock returns over the short and long-term violates the efficient market hypothesis. In response to these studies, Fama reviewed once again the market efficiency literature in 1991, offering his views on what he had learned from the research on market efficiency.

The 1991 review also divided work on market efficiency into three categories, but they somewhat differed from the categories identified in the 1970 paper. The main difference was in the first category: instead of weak form tests (which are only concerned with the forecast power of past returns), the first category covered the more general area of tests for return predictability, which also included the work on forecasting returns with variables like dividend yields and interest rates. For the second and third categories, he only proposed changes in title, not coverage, naming them event studies and tests for private information, respectively.

Fama (1991) stated that ‘ambiguity about information and trading costs is not the main obstacle to inferences about market efficiency’. He believed that the joint-hypothesis problem was more serious. Thus, market efficiency per se is not testable; it must be tested jointly with some model of equilibrium, an asset pricing model. This point says that one can only test whether information is properly reflected in prices in the context of a pricing model that defines the meaning of “properly”. As a result, he concluded that when one ‘finds anomalous evidence on the behavior of returns, the way it should be split between market inefficiency or a bad model of market equilibrium is ambiguous’.

Finally, Fama also raised a very important question: Does return predictability reflect rational variation through time in expected returns, irrational deviations of price from fundamental value, or some combination of the two? Additionally, Fama (1998) stated that it was time to ask whether the recent studies on long-term returns that suggested market inefficiency also suggested that efficiency should be discarded. His answer was a strong no: an efficient market generates categories of events that individually suggest that prices overreact to information. But in an efficient market, under-reaction will be about as frequent as overreaction. If anomalies split randomly between under-reaction and overreaction, they are consistent with market efficiency.

Thaler (1999) also addressed this issue. On the one hand, he believes that real financial markets do not resemble the ones one could imagine if we only read finance textbooks. But, on the other hand, he sustains that there is compelling evidence that markets are efficient, and that is the performance of active fund managers. In short, he believes that although market behavior often diverges from what would be expected in a rational efficient market, these anomalies do not create such large profit opportunities so that active fund managers as a group can earn abnormal returns.

However, an alternative explanation for why active money managers may underperform passive money managers can be offered based on overconfidence. Odean (1998) believes that active money managers may be overconfident in their ability to beat the market and spend too much time and money trying to do so. When information is costly, overconfident traders who actively pursue information fare less well than passive traders.

Can the efficient market hypothesis be discarded?

An important defense against market efficiency is that the anomalies literature has not settled on a specific alternative to market efficiency; it only points out that market inefficiency occurs. For example, the anomalies literature has not accepted the discipline of overreaction to be the prediction of a behavioral finance alternative to market efficiency. If apparent overreaction was the general result in studies of long-term returns, market efficiency

would be dead, replaced by the behavioral alternative of overreaction. However, the anomalies literature has found that under-reaction is about as frequent. For example, there is evidence that stock prices seem to respond to earnings announcements for quite some time after they are announced (post earnings announcement drift and post recommendation drift).¹⁸

The market efficiency hypothesis offers an answer to the question regarding why the market overreacts in some instances and under-reacts in others, and that is chance. As Fama (1998) explains, ‘the expected value of abnormal returns is zero, but chance generates apparent anomalies that split randomly between overreaction and under-reaction. In other words, Fama believes that apparent overreaction of stock prices to information is about as common as under-reaction, and this is consistent with the market efficiency hypothesis that the anomalies are chance results (although “behavioralists may argue that it is possible to distinguish chance from systematic cognitive bias because the behavioral literature does not simply say that people do not behave exactly as the traditional model predicts; it says that people behave in specific, regular, predictable ways that are inconsistent with the traditional models).

As a result, Fama (1998) believes that the behavioral literature does not lean cleanly towards either anomaly (under-reaction vs. overreaction) as the behavioral alternative to market efficiency. So, is the weight of the evidence on long-term return anomalies so big that market efficiency is not a viable working model even in the absence of an alternative model that explains both under and overreaction?

Thaler (1999) also refers to this issue. Even though his 1999 study shows that the premise of behavioral finance –that cognitive biases may influence asset prices-is at least theoretically possible, he wonders if it is worth the trouble. Specifically, he wonders: What is the evidence that traditional models cannot do the job? In other words, is there enough evidence to undermine the rational efficient market paradigm?

Statman (1999) also believes that market efficiency is at the center of the battle between standard finance and behavioral finance, and that overreaction and under-reaction are “weapons” in this battle. But he continues by making a distinction between two meanings of the term “market efficiency”.

One meaning is that investors cannot systematically beat the market. The other is that security prices are rational. Rational prices reflect only utilitarian characteristics, such as risk, not value expressive characteristics, such as sentiment. He continues by stating that behavioral finance has shown, however, that value-expressive characteristics matter in both investor choices and asset prices. Therefore, the market efficiency battle is being fought as if one side can only win if the other loses. Statman believes that ‘the discipline of finance would do well to accept the first meaning of market efficiency and reject the notion that security prices are rational...we could then stop fighting the market efficiency battle and focus on exploring (i) asset pricing models that reflect both value expressive and utilitarian characteristics and (ii) the benefits, both utilitarian and value expressive, that investment professionals provide to investors’. He concludes by arguing that today’s standard finance is so weighted down by anomalies that reconstructing financial theory along behavioral lines makes a lot of sense. But, as Ray Ball explains (Chew, 1999), ‘the theory of efficient markets was an audacious and welcome change from the comparative ignorance of stock markets behavior that preceded it: and despite its now obvious theoretical and empirical flaws, it has profoundly influenced both the theory and practice of finance’.

What does Behavioral Finance have to offer?

Given such limitations in the concept of market efficiency and the existing empirical tests of the theory, a group of finance scholars known as “behavioralists” has suggested that it is time to abandon the premise of collectively rational investors on which the theory rests. “Behavioralists” argue that stock price corrections and cycles reflect systematic biases in how investors use information (Chew, 1999). But is behavioral finance the answer to the limitations of the efficient markets theory?

What we do know is that Behavioral Finance offers an alternative paradigm to the efficient market theory, one in which individuals make systematic mistakes in the way they process information (Daniel and Titman, 1999).

The main conclusion is that investors’ behaviors can influence asset

prices. Investors do not behave with extreme rationality and research has shown that investors' deviations from rationality are often systematic. The main advantage of Behavioral Finance is that it relaxes the traditional assumptions of financial economics by incorporating these observable, systematic, and human departures from rationality into standard models of financial markets (Barber and Odean, 1999).

Thaler (1999) also believes that behavioral finance enriches the understanding of financial markets by 'adding a human element'. But can behavioral finance be theorized? Thaler mentions three groups of authors (Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999) who have generated asset-pricing models that try to explain the pattern of the latest empirical results: returns that exhibit under-reaction in the short run and overreaction in the long run. These studies draw on results from psychology to motivate the behavior of the agents in their models. As a result, financial economists are becoming accustomed to thinking about the role of human behavior in driving stock prices.

V. Behavioral Finance: Future Steps for Research

So, what are the next steps Behavioral Finance should follow? Today, research has increased and there is abundant evidence that violates the traditional finance theory. However, there is still no widely used model that incorporates all these anomalies. Several models have been proposed that take into account different behavioral factors, but none of them is as popular as, for example, the CAPM once was. Consequently, and following Statman's (1999) advice, the existing behavioral models should continue to be analyzed, making adjustments as new anomalies or new criticisms to the existing models appear.

The idea of Behavioral Finance is to extend the models of financial markets by incorporating the imperfections that we observe in the market. But how can these factors be incorporated in the models? Shefrin and Statman (1994) developed a behavioral asset pricing theory as an analog to the standard CAPM. The behavioral asset pricing model (BAPM) features the market

interaction of two groups of traders: information traders and noise traders. Information traders are the ones present in the standard CAPM and they are free of cognitive errors and have mean-variance preferences. Noise traders live outside the CAPM, commit cognitive errors, and do not have strict mean-variance preferences.

The expected returns of securities in the BAPM are determined by their “behavioral betas”, which are relative to the tangent mean-variance efficient portfolio. But the mean-variance efficient portfolio is not the market portfolio because noise traders affect security prices.

When prices are efficient, security prices and volatility are determined through a single driver, a sufficient statistic consisting only of new information. The single driver drives the mean-variance efficient frontier, the return distribution of the market portfolio, the premium for risk, the term structure, and the price of options. However, noise traders act as a second driver and they steer the market away from price efficiency. When prices are inefficient, new information is no longer a sufficient statistic. Old information continues to affect prices, volatility, the premium for risk, the term structure and the option prices.

In 1995, these same authors used a behavioral method of security valuation to better understand size and book-market ratios, and beta and its correlation to stock returns. The study provided empirical evidence on how investors reached expectations about stock returns and related the data to realized returns.

In 1996, Fama and French developed the “three factor model” to try to explain behavioral factors. Previous work had shown that average returns on common stocks were related to firm characteristics like size, earnings/price, cash flow/price, book to market equity, past sales growth, long term past return, and short term past returns. Because these patterns in average returns were apparently not explained by the CAPM, they were called anomalies. The authors found that, except for the continuation of short term returns, the anomalies largely disappeared in the three factor model. Although this model could not explain the continuation of short term returns documented by Jegadeesh and Titman (1993), they captured the reversal of long term returns documented by De Bondt and Thaler (1985, 1987).

In 1999, Shefrin and Statman developed a behavioral portfolio theory as an alternative to the Markowitz mean-variance portfolio. Mean variance investors evaluate portfolio as a whole; they consider covariances between assets as they construct their portfolios. They also have consistent attitudes towards risk; they are always risk averse. Behavioral investors build portfolios as pyramids of assets, layer by layer. The layers are associated with particular goals and attitudes towards risk. Some money is in the downside protection layer, designed to avoid poverty, and other is in the upside potential layer, designed for a shot at being rich.

Finally, another factor that has been largely documented by the behavioral finance literature and incorporated in their models is sentiment. According to Behavioral Finance, sentiment is the reflection of heuristic-driven bias. For example, in 1998, Barberis, Shleifer and Vishny presented a model of investor sentiment, which was consistent with the empirical findings. In other words, their work tried to model how investors formed beliefs. The model was based on psychological evidence and produced both under-reaction and overreaction for a wide range of parameter values.

Moreover, several sentiment indexes were developed to measure sentiment in the market. Traditionally, market sentiment is seen as a contrarian indicator. Markets rise, the theory goes, as bears become bulls and put money into the market. The market peaks when there are no bears left and everyone is invested. As a result, The Bullish Sentiment Index ($\# \text{ bulls} / (\# \text{ bulls} + \# \text{ bears})$) is used as a contrarian indicator. Research shows that the BSI provides no guidance as to where the market is headed next but it does a good job of predicting the past.¹⁹

Moving Forward

As Merton (1987) emphasizes, ‘anomalous empirical evidence has indeed stimulated wide-ranging research efforts to make explicit the theoretical and empirical limitations of the basic finance model with its frictionless markets, complete information, and rational, optimizing economic behavior...but although much has been done, this research line is far from closure’. In short,

future research should focus in comparing the existing behavioral models and strategies with the traditional model, trying to answer the following questions: (1) How are portfolios designed in practice? (Active management) (2) Do these portfolios deviate from the “efficient portfolios” identified by the Markowitz model? Are behavioral models taken into account in portfolio selection? (3) How do “behavioral models and strategies” behave compared to the traditional model and to active management; i.e. which portfolio strategy delivers superior performance? (4) Are contrarian strategies the answer? (5) How does passive management compare to these results? (6) Do the results vary with the sample period? (7) What happens if these models are tested in less efficient markets such as Argentina? (8) Is it worth incorporating behavioral factors into models?

In order to answer the first two questions, the way fund managers construct their portfolios in practice could be analyzed. Natalia del Águila and María Galli (1998) showed that fund managers (not only from Argentina but also from Europe and the United States) did not use the model developed by Markowitz to form their portfolios, claiming that the main setback of this model was the estimation of the stocks’ expected returns.

Additionally, the research on Active Management has increased considerably over the years. According to this research, instead of using traditional models of portfolio selection, fund managers implement Active Management. This method consists in several steps: (1) choosing the type of analysis to be used in security selection, which can be strictly fundamental, strictly technical, or a combination of both; (2) deciding if the fundamental analysis should follow a “Top Down” or “Bottom Up” approach; and (3) choosing the investment criteria to be followed (value vs. growth).

Future research should try to find out if, as a result of the growing literature in behavioral finance, behavioral models are now taken into account in portfolio selection. Then, behavioral models and strategies should be compared to the traditional model and to active management, trying to address which portfolio strategy delivers superior performance and if it is worth incorporating behavioral factors into the models.

For example, a potential empirical study could be as follows:

1. **Traditional Model:** in order to test the traditional model, portfolios created according to Markowitz's portfolio optimization model could be used. The inputs necessary to calculate the efficient frontier are expected return and volatility of each stock, as well as the correlation between them. Prices for stocks listed in the New York Stock Exchange (NYSE) for the period starting in January 1990 could be used to calculate these inputs, and the "PCF Toolkit" software could be used to calculate the efficient portfolios.
2. **Active Management:** the return of US Equity Mutual Funds could be considered to test the performance of Active Management over the years and to be able to compare it to alternative models.
3. **"Behavioral" Strategies:** to test the behavioral strategies, several tests could be carried out. To test for overconfidence, the approach used by Barber and Odean (1999) could be replicated. In their paper, they tested whether investors with accounts at discount brokerages traded excessively. Their approach was to determine whether the securities bought by the investors outperformed those they sold by enough to cover the costs of trading. They examined return horizons of 4 months, one year and two years following each transaction. This same methodology could be applied to US equity mutual funds, analyzing if the securities they buy outperform the ones they sell by enough to cover trading costs. Additionally, different time horizons could be used, analyzing the responses in the short, medium and long term.

In order to test for overreaction, the work done by De Bondt and Thaler (1985) could be extended. Their two hypotheses were that extreme movements in stock prices would be followed by subsequent price movements in the opposite direction, and that the more extreme the initial price movement, the greater would be the subsequent adjustment. In order to test these hypotheses, portfolios of the most extreme winners and most extreme losers could be formed (winner and loser portfolios) using return data for New York Stock Exchange (NYSE) common stocks for the period starting in January 1990. Furthermore, to address the issue of the relationship between risk and return, portfolio CAPM betas could also be compared.

To test for mean reversion, De Bondt and Thaler's work (1989) as well as Lehman's work (1990) could be extended. The former showed that (i) the returns for both winners and losers were mean-reverting; and (ii) the five-year price reversal for losers was more pronounced than for winners. In addition, and consistent with overreaction, they showed that the more extreme the initial price movements, the greater the subsequent reversals. Lehman (1990) showed that short term reversals could also be observed. His results showed that the "winners" and "losers" one week experienced sizeable return reversals the next week in a way that reflected arbitrage profits. Consequently, and in order to test for short, medium and long term price reversal, portfolios composed of either winners or losers should be tested over a specific time horizon, which could include 1 week, 3 months, 6 months, 12 months, 3 years and 5 years. The sample data mentioned in the previous point could be used to form the portfolios.

Also, and based on the previous findings, contrarian and relative strength strategies should be evaluated. Contrarian strategies consist in buying past losers and selling past winners. On the other hand, relative strength strategies consist in buying past winners and selling past losers. Jegadeesh and Titman (1993) tested the inverse trading strategy proposed by De Bondt and Thaler in 1985 (contrarian strategy), providing an analysis of relative strength trading strategies over 3 to 12 month horizons. The results of the study showed that trading strategies that bought past winners and sold past losers realized significant abnormal returns over the 1965 to 1989 period. So, which trading strategy is more profitable? In order to be able to compare them, the time horizons used in both strategies should be the same. For example, trading strategies based on very short-term return reversals (1 week or 1 month), or very long-term return reversals (3 to 5 years) as well as strategies based on price movements over the past 3 to 12 months should be considered.

Finally, additional tests could (i) compare these results to the performance of passive management; (ii) evaluate the performance of these strategies if the sample period is changed; and (iii) replicate the analysis in less efficient markets such as Argentina.

In conclusion, the major factors driving portfolio selection are much more complex than the mean and variance of future returns and the efficient frontier. Empirical research has shown that, when selecting a portfolio, investors not only consider statistical measures such as risk and return, but also psychological factors such as sentiment, overconfidence and overreaction. In short, heuristic-driven bias, frame dependence, and market inefficiency shape the kind of portfolios that investors chose, the type of securities investors find attractive, and the biases to which investors are subject.

NOTES

- 1 For further discussions on systematic risk, see Sharpe (1964)
- 2 Kahneman and Tversky (1979) developed the Prospect Theory, which presented a model of decision making that was an alternative to subjective expected utility theory with more realistic behavioral assumptions.
- 3 Odean's main contribution was to successfully model overconfidence based on past models. See Odean (1998) for literature on related work on overconfidence.
- 4 For research on excess volatility in equity markets, see Shiller (1981, 1989), LeRoy and Porter (1981), Kleidon (1986), and Marsh and Merton (1986).
- 5 Additionally, some have argued that the results can be explained by the systematic risk of their contrarian portfolios and the size effect. See Chan (1988), Ball and Kothari (1989), Zarowin (1990), and Chopra, Lakonishok, and Ritter (1992).
- 6 De Bondt and Thaler were not the first ones to analyze mean reversion. In order to prove the random walk hypothesis, Fama and French (1988) regressed the return on a stock market index over some time period of length T , on returns over the prior period of equal length. If prices followed a random walk, then the slope in the regression would be zero. If prices were mean reverting, then the slope would be negative. The results revealed considerable mean reversion: the slopes of the regressions were generally negative for horizons from 18 months to 5 years.
- 7 For a more detailed explanation of these studies, see De Bondt and Thaler (1989), pp.197.
- 8 Fama and French (1986) conclude that 'The tendency toward reversal...may reflect time-varying expected returns generated by rational investor behavior and the dynamics of common macroeconomic driving variables. On the other hand, reversals generated by a stationary component of prices may reflect market-wide waves of overreaction of the kind assumed in models of an inefficient market...Whether predictability reflects market inefficiency or time-varying expected returns generated by rational investor behavior is, and will remain, an open issue'.

- 9 For further evidence on systematic reversals in stock returns over longer intervals, see Fama and French (1988) and Poterba and Summers (1988).
- 10 Joseph Livingston has collected various stock market forecasts from academic, business, and government economists. Early June and early December of each year since 1952, about forty economists predict the level of the S&P that will prevail at the end of the following June and December.
- 11 For further evidence on systematic reversals in stock returns over the short term, see Rosenberg, Reid, and Lanstein (1985), and Jegadeesh (1987).
- 12 Some have argued that the results could be explained by the systematic risk of their contrarian portfolios and the size effect: see Chan (1988), Ball and Kothari (1989), Zarowin (1990), and Chopra, Lakonishok, and Ritter (1992).
- 13 See also Levy (1967) and Jensen and Bennington (1970).
- 14 See Jegadeesh and Titman (1991) and Lo and MacKinlay (1990) for supports of the short term interpretation.
- 15 See Levy (1967), Jensen and Bennington (1970), and Grinblatt and Titman (1989, 1993).
- 16 Additionally, they stated that: 'The evidence of initial positive and later negative relative strength returns suggests that common interpretations of return reversals as evidence of overreaction and return persistence (i.e., past winner achieving positive returns in the future) as evidence of under-reaction are probably overly optimistic. A more sophisticated model of investor behavior is needed to explain the observed patten of returns'.
- 17 See Basu (1977) for the US and Chan, Hamao and Lakonishok (1991) for Japan.
- 18 For further research on under-reaction to earnings' announcements, see Bernard and Thomas (1989, 1990), Shefrin (1998), Bernard (1993), Mendenhall (1991), Abarbanell and Bernard (1992), Wiggins (1991), Amir and Ganzach (1998), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998, 2001), Hong and Stein (1999), Womack (1996).
- 19 Other Sentiment Indicators have been developed throughout the years. The American Association of Individual Investors (AII) monitors the sentiments of small investors; the Richard Bernstein Index is based on Wall Street strategists' allocations; the Call/Put ratio is used by some technical analysts to measure sentiment (see Shefrin (1998), Meyers (1989, 1994) and Billingsley and Chance (1988); Discount on closed-end funds can also serve as a sentiment index (Shefrin, 1998).

REFERENCES

- Abarbanell, J. S. and Bernard, V. L. 1992. "Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior", *The Journal of Finance* 45:3 (July): 1181-1207.
- Amir, E. and Ganzach, Y. 1998. "Overreaction and underreaction in analysts Forecast", *Journal of Economic Behavior and Organization*, 37, 333-347.

- Ball, R. and Kothari, S. 1989. "Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlation in Returns", *Journal of Financial Economics* 25, 51-74.
- Barber, Brad M. and Odean, Terrance. 1999. "The Courage of Misguided Convictions", *Financial Analysts Journal*, November/December.
- Barberis, Nicholas, Shleifer, Andrei and Vishny, Robert. 1998. "A model of investor sentiment", *Journal of Financial Economics* 49, 307-343.
- 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*, vol.32, no.3 (July), 663-682.
- Bernard, V. L. and Thomas, J. K. 1989. "Post-earnings- announcement drift: delayed price response or risk premium?", *Journal of Accounting Research* 27 (Supplement): 1-36.
- Bernard, V. L. and Thomas, J. K. 1990. "Evidence that stock prices do not fully reflect the implications of current earnings for future earnings", *Journal of Accounting and Economics* 13: 305-340.
- Bernard, V. L. 1993. "Stock price reactions to earnings announcements: a summary of recent anomalous evidence and possible explanations", *Advances in Behavioral Finance*, Richard H. Thaler, Editor, 303-340.
- Billingsley, Randall S. and Chance, Donald. 1988. "Put-Call Ratios and Market Timing Effectiveness." *Journal of Portfolio Management* (fall) 15, no.1: 25-28.
- Bremer, M.A. and Sweeney, Richard J. 1988. "The Information Content of Extreme Negative Rates of Return", Working Paper, Claremont McKenna College, February.
- Chan, Louis K.C., Hamao, Yasushi, and Lakonishok, Josef. 1991. "Fundamentals and Stock Returns in Japan", *Journal of Finance*, vol.46, no.5 (December), 1739-64.
- Chan, K.C. 1988. "On the Contrarian Investment Strategy", *Journal of Business*, 61, pp. 147-163.
- Chan, K.C.. 1986. "Can Tax-Loss Selling Explain the January Seasonal in Stock Returns?", *Journal of Finance* 41(5).
- Chew, Donald H., Jr. 1999. *The New Corporate Finance: Where Theory Meets Practice*, McGraw-Hill Companies, chapters 1-6.
- Chopra, Navin, Lakonishok, Josef and Ritter, Jay R. 1992. "Measuring abnormal performance: Do stocks overreact?", *Journal of Financial Economics* 31, 235-268.
- Daniel, Kent and Titman, Sheridan. 1999. "Market efficiency in an irrational world", *Financial Analysts Journal*, Nov-Dec, 28-55.

- Daniel, Kent, Hirshleifer, David and Subrahmanyam, Avaniidhar. 1998. "Investor psychology and security market under- and overreactions", *Journal of Finance*, Vol. 53 Issue 6 (Dec), 1839-1885.
- Daniel, Kent, Hirshleifer, David, and Subrahmanyam, Avaniidhar. 2001. "Overconfidence, arbitrage, and equilibrium asset pricing", *Journal of Finance* 56, 921-965.
- Daniel, Kent. 2002. "Behavioral Finance". Financial Executives International Conference, April 2002.
- De Bondt, Werner. 1991. "What do economists know about the stock market?" *Journal of Portfolio Management* 17, 2:84-91.
- De Bondt, Werner. 1993. "Betting on Trends: Intuitive Forecast of Financial Risk and Return." *International Journal of Forecasting*, 9: 355-371.
- De Bondt, Werner. 1998. "A Portrait of the Individual Investor" *European Economic Review* 42: 831-844.
- De Bondt, Werner, and Thaler, Richard. 1985. "Does the stock market overreact?", *Journal of Finance* 40: 793-805.
- De Bondt, Werner, and Thaler, Richard. 1987. "Further Evidence on Investor Overreaction and stock market seasonality", *Journal of Finance* 42: 557-581.
- De Bondt, Werner, and Thaler, Richard. 1989. "A Mean Reverting Walk Down Wall Street". *Journal of Economic Perspectives* 3, no.1: 189-202.
- De Bondt, Werner, and Thaler, Richard. 1990. "Do security analysts overreact?", *American Economic Review*, 80, 2: 52-57.
- del Aguila, Natalia, and Galli, María. 1998. "Theory and Practice: Harry Markowitz's Legacy to Portfolio Management in Argentina", Working Paper, Universidad Torcuato Di Tella, Argentina.
- Einhorn H. J. and Hogarth, R. 1978. "Confidence in Judgment: Persistence in the Illusion of Validity". *Psychological Review*, 85, no. 5: 395-416.
- Fabozzi, Frank. 1998. *Active Equity Portfolio Management*, Frank J. Fabozzi Associates, New Hope, Pennsylvania.
- Fama, Eugene and French, Kenneth. 1986. "Common Factors in the Serial Correlations of Stock Returns", Working Paper, Grad. School of Business, Univ. of Chicago, October.
- Fama, Eugene and French, Kenneth. 1988. "Permanent and temporary components of stock prices". *Journal of Political Economy*, 96: 246-273.
- Fama, Eugene and French, Kenneth. 1996. "Multifactor explanations of asset pricing anomalies", *Journal of Finance*, 51, 1: 55-84.

- Fama, Eugene. 1965. "Random Walks in Stock Market Prices", *Financial Analysts Journal*, Sep-Oct, p.4.
- Fama, Eugene. 1970. "Efficient capital markets: a review of theory and empirical work", *Journal of Finance*, 25, 2:383-417.
- Fama, Eugene. 1991. "Efficient capital markets II", *Journal of Finance*, 46, 5: 1575-1618.
- Fama, Eugene. 1998. "Market efficiency, long-term returns, and Behavioral Finance", *Journal of Financial Economics*, 49, 3: 283-306.
- Fiske, Susan T. and Taylor, Shelley E. 1991. *Social Cognition*, McGraw Hill, Inc., NY.
- Frank, Jerome D. 1935. "Some psychological determinants of the level of aspiration", *American Journal of Psychology*, 47, 285-293.
- Fuller and Thaler Asset Management, 2007. "Quarterly Update", accessed from <http://www.fullerthaler.com/reviews/newsltr2007Q1.pdf>
- González Isla, Pablo. 2006. *No le tema a Wall Street: Una mirada estratégica, integral y sencilla al mundo de las inversiones financieras*, Editorial Planeta, Argentina
- Graham, Benjamin and Dodd, David. 1934. *Security Analysis*, New York-London: Whittlesey House (McGraw Hill).
- Grether, David M. 1980. "Bayes's rule as a descriptive model: The representative heuristic", *Quarterly Journal of Economics*, 95, 537-557.
- Grinblatt, Mark, and Titman, Sheridan. 1989. "Mutual fund performance: An analysis of quarterly holdings", *Journal of Business*, 62, 393-416.
- Grinblatt, Mark and Titman, Sheridan. 1993. "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns", *Journal of Business*, 66,1:47-68.
- Hong, Harrison, and Stein, Jeremy C. 1999. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets", *Journal of Finance*, 54, 2143-2184.
- Jegadeesh, Narasimhan, and Titman, Sheridan. 1991. "Short horizon return reversals and the bid-ask spread", Working Paper, University of California at Los Angeles.
- Jegadeesh, Narasimhan, and Titman, Sheridan. 1993. "Returns to Buying Winners and Selling Losers: Implications for stock market efficiency". *Journal of Finance* 48: 65-91.
- Jegadeesh, Narasimhan. 1987. "Evidence of the Predictability of Equity Returns", Graduate School of Business, Columbia University.
- Jegadeesh, Narasimhan. 1990. "Evidence of Predictable Behavior of Security Returns," *Journal of Finance*, 45, 3:881-98.

- Jensen, Michael, 1999. "Self-Interest, Altruism, Incentives, and Agency Theory", in Chew (1999).
- Jensen, M.C. and Bennington, G. 1970. "Random Walks and Technical Theories: Some Additional Evidences", *Journal of Finance*, 25 (May), 469-482.
- Kahneman, Daniel and Tversky, Amos. 1973. "On the psychology of prediction", *Psychological Review*, 80, 237-251.
- Kahneman, Daniel and Tversky, Amos. 1979. "Prospect Theory: An analysis of Decision Making Under Risk". *Econometrica* 47, 2:263-291.
- Kahneman, Daniel, Slovic, Paul and Tversky Amos, 1982. *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press, Cambridge, and NY.
- Kleidon, Allan W. 1986. "Variance bounds tests and stock price valuation models", *Journal of Political Economy*, 94, 953-1001.
- Kunda, Ziva, 1987. "Motivated inference: Self-serving generation and evaluation of causal theories", *Journal of Personality and Social Psychology*, 53, 636-647.
- LeDoux, Joseph. 1994. "Emotion, Memory and the Brain", *Scientific American*, Vol.270, 50-57.
- Lehmann, Bruce. 1990. "Fads, Martingales, and Market Efficiency." *Quarterly Journal of Economics*, 105: 1-28.
- LeRoy, Stephen F. and Porter, Richard D. 1981. "Stock price volatility: tests based on implied variance bounds", *Econometrica* 49, 97-113.
- Levy, R. A. 1967. "Random Walks: Reality or Myth?" *Financial Analysts Journal*, 23, 6:69-77.
- Lichtenstein, Sarah, Fischhoff, Baruch, and Phillips, Lawrence. 1982. "Calibration of probabilities: The state of the art to 1980", in Kahneman, Slovic, Tversky (1982).
- Lo, A.W., and MacKinlay, C. 1990. "When are contrarian profits due to stock market overreaction?", *The Review of Financial Studies*, 3, 175-205.
- Lopes, Lola. 1987. "Between Hope and Fear: The Psychology of Risk". *Advances in Experimental Social Psychology*, 20: 255-295.
- Lord, Charles G., Ross, Lee, and Lepper, Mark R. 1979. "Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence", *Journal of Personality and Social Psychology*, 37, 2098-2109.
- Markowitz, Harry. 1952. "Portfolio Selection", *Journal of Finance*, March, 77-91.
- Marsh, Terry A. and Merton, Robert C. 1986. "Dividend Variability and variance bounds tests for the rationality of stock market prices", *American Economic Review*, 76, 483-498.

- Mendenhall, Richard. 1991. "Evidence of possible underweighting of earnings-related information," *Journal of Accounting Research*, 29, 170-140.
- Merton, Robert. 1987, "A simple model of capital market equilibrium with incomplete information", *Journal of Finance*, 42, 3: 483-510.
- Meyers, Thomas A. 1989. *The Technical Analysis Course: A Winning Program for Stock and Future Traders and Investors*, Probus. Chicago.
- Nisbett, Richard E., and Ross Lee. 1980. *Human Inference: Strategies and shortcoming of social judgment*, Prentice Hall, Englewood Cliffs, NJ.
- Odean, Terence. 1998. "Volume, volatility, Price, and Profit When All Traders Are Above Average". *Journal of Finance*, 53: 1887-1934.
- Olsen, Robert A. 1998. "Behavioral Finance and Its Implications for Stock-Price Volatility." *Financial Analysts Journal*, March/April, 10-18.
- Poterba, James M. and Summers, Lawrence H. 1988. "Mean Reversion in Stock Prices: Evidence and Implications". *Journal of Financial Economics*, 27-59.
- Raghubir, Priya, and Ranjan Das, Sanjiv, 1999. "A Case for Theory-Driven Experimental Enquiry", *Financial Analysts Journal*, Nov/Dec.
- Rosenberg, Barr, Reid, Kenneth, and Lanstein, Ronald. 1985. "Persuasive Evidence of Market Inefficiency", *Journal of Portfolio Management*, 9-16.
- Sharpe, William F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk", *Journal of Finance*, 19, September, 425-442.
- Sharpe, William F. 1985. *Investments*, Prentice-Hall, Inc., Englewood Cliffs, New Jersey.
- Shefrin, Hersh and Statman, Meir. 1994. "Behavioral Capital Asset Pricing Theory." *Journal of Financial and Quantitative Analysis*, 29, 3:323-349.
- Shefrin, Hersh and Statman, Meir. 1995. "Making Sense of Beta, Size, and Book-to-Market." *Journal of Portfolio Management* 21, 2: 26-34.
- Shefrin, Hersh and Statman, Meir. 2000. "Behavioral Portfolio Theory", *Journal of Financial and Quantitative Analysis*, Vol. 35, 2.
- Shefrin, Hersh. 1998. *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*, Harvard Business School Press.
- Shiller, Robert J. 1979. "The Volatility of Long-term Interest Rates and Expectations Models of the Term-Structure". *Journal of Political Economy*, 87: 1190-1219.
- Shiller, Robert J. 1981. "Do stock prices move too much to be justified by subsequent changes in dividends?", *American Economic Review* ,71, 3: 421-498.

- Shiller, Robert J. 1989. *Market Volatility*, MIT Press, Cambridge, Mass.
- Shleifer, Andrei and Vishny, Robert. 1990. "Equilibrium short horizons of investors and firms", *American Economic Review*, 80, 2:148-153.
- Statman, Meir. 1999. "Behavioral Finance: Past Battles and Future Engagements", *Financial Analysts Journal*, November/December.
- Taylor, Shelley, and Brown, Jonathon D. 1988. "Illusion and well-being: A social psychological perspective on mental health", *Psychological Review*, 89, 155-191.
- Thaler, Richard H. 1999. "Mental Accounting Matters." *Journal of Behavioral Decision-making*, 12:183-206.
- Vermaelen, Theo and Verstringe, Marc. 1986. "Do Belgians Overreact?" Working Paper, Catholic University of Louvain, Belgium, November.
- Weinstein, Neil. 1980. "Unrealistic Optimism About Future Life Events." *Journal of Personality and Social Psychology*, 39, 5:806-820.
- Wiggins, J. B. 1991. "Do Misperceptions about the Earnings Process Contribute to Post-Announcement Drift?", Working Paper, Cornell University .
- Womack, Kent. 1996. "Do Brokerage Analysts' Recommendations Have Investment Value?" *Journal of Finance* 51, 1: 137-168.
- Zarowin, P. 1990. "Size Seasonality, and Stock Market Overreaction", *Journal of Financial and Quantitative Analysis*, 25, 113-125.