# Comparative analysis of individual investor portfolios based on behavioral finance and efficient market theories

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**ABSTRACT**

This quantitative study compared the effectiveness of two investment strategies with regards to return on investment (ROI). One investment strategy was based on behavioral finance theories of price momentum and was compared to an equally valued investment strategy based on the efficient market theory. Price momentum (rapid acceleration in asset price) was based on the behavioral theory of positive reinforcement. The behavioral finance theory strategy was represented by a momentum strategy based on crossing moving averages. The DOW 30 represented the efficient market theory. This researcher sought to identify if knowledge gained from recent studies in behavioral finance could be translated into a strategy that could enable the individual investor to fare better than the efficient market theory proxy of buying and holding the DOW 30. The study involved a quantitative quasi-experiment method utilizing an interrupted time series with nonequivalent no-treatment control group time series. Analysis of covariance with a single covariate (ANCOVA) was also employed. Data was taken from the Internet provider, Trade Station Brokerage. The stocks came from companies listed on the New York Stock Exchange and NASDAQ, which have mid-size and large capitalizations. The momentum portfolios were selected by observing monthly charts with the shorter period moving average crossing upward from below the longer period moving average. The strategy was based on pattern recognition and requires no analysis of corporate financial or accounting data. The study proved the alternative hypothesis by modeling momentum portfolios and testing them against the buy and hold efficient market proxy for 1year and greater. The results of the ANCOVA presented support that not all groups are the same. The analysis showed that the group variable significantly differentiates the percentage change in ROI after 1 year of investment ($F = 5.129$, $p = .004$; $F = 4.518$, $p = .016$). All momentum portfolios tracked by time series analysis significantly outperformed the buy and hold efficient market proxy. Knowledge of behavioral finance can help investors to form profitable strategies, and should be encouraged in business schools and among individual investors. Future research should be directed at behavioral finance for both buying and selling equities.

Keywords: Anchoring bias, Bear market, Behavioral finance theory, Efficient market theory, Herding, Illiquid, Moving average convergence divergence (MACD), Resistance point, Support point

## INTRODUCTION:

After the U.S. stock market collapse of 1987, the extraordinary rise in prices of technology stocks, the subsequent decline of the market in 2000, and the financial crisis of 2008, several researchers shifted their support from the efficient market theory (the idea that an asset's price reflects all information, thus investors have difficulty outperforming the market) to a behavioral finance theory (De Bondt, Muradoglu, Shefrin, & Stalkouras, 2008). Behavioral finance theorists study the quality and nature of financial choices made by individuals and investigate the subsequent economic results (De Bondt et al., 2008). Advocates of the behavioral finance theory argue that markets are not purely efficient because individuals making financial judgments are subject to emotions, such as fear and greed (Smith, 2008). Individuals are also subject to varying degrees of education and appetite for risk, and have different backgrounds that could render their behavior less than rational (Victoravich, 2010). Americans lost $7.4 trillion U.S. in stock wealth from July 2008 to March 2009 and $3.4 trillion U.S. in real estate for the same period (Swagel, 2009). Partially due to these events, investors have lost confidence in the professional investment industry, the professionals that represent securities, and the investment products they represent (Redhead, 2011).

Individuals acting alone with varying degrees of competence, lack strategies to ensure profitability (Chandra, 2009). Because individuals on their own lack strategies, an argument can be made that behavioral finance theory has the potential to create value for society and for individuals by aiding individuals with strategy development. Much of the recently published research on behavioral finance theory originated in countries other than the U.S. (Assogbavi, Giguere, & Sedzro, 2011; Azizan, Mohamed, & Phooi M'ng, 2011; Liu, Liu, & Ma, 2011). Many researchers have developed investment strategies based on behavioral finance theory that are accepted by fund managers and financial professionals (Nikiforow, 2010). In America, the majority of the research into strategies derived from behavioral finance theory has been directed privately toward institutions, such as Wells Fargo, Merrill Lynch, Vanguard, Fidelity, and large pension plans, and has not been directed toward individual investors (Fox, 2009). However, laws concerning individual retirement accounts have changed, making self-directed 401Ks popular. De Bondt et al. (2008) called for further research focused on making practical use of what has been learned in behavioral finance theory.

In contrast to the behavioral finance theory, the efficient market theory indicates that the market price of a share of a company's stock reflects the expectations and the knowledge of investors. Supporters of this theory argue that searching for undervalued stocks or attempting to forecast market movements is ineffectual because all developments and projections are efficiently reflected in the price of a stock (Chiang, Ke, Liao, & Wang, 2012). An investor could do as well or better with a buy-and-hold strategy of arbitrary stocks (Mishkin & Eakins, 2009). The efficient market theory is popular in the financial industry because of the long-term capital gains tax advantages it confers and because portfolios, based on this theory, require less attention as they are often based on buy-and-hold strategies. The efficient market theory is still at the center of market analysis for researchers in the financial community and for investment strategy for individual investors (Yalamova & McKelvey, 2011).

## BACKGROUND

The efficient market theory has not been reliable for the individual investor due to rapid volatility in the market place (De Bondt et al., 2008). Individual investors have lost confidence in equity markets in general and in those who represent market products (Redhead, 2011). With the growth of online brokerage, many individuals have moved away from traditional brokerage and have chosen to actively manage their own accounts. Changes in the law concerning retirement accounts have promoted the growth in the online industry. Many individual investors lack adequate education and strategy skills to stay profitable (Chandra, 2009).

Keynes' (1964) observation that investors calculate where they can, but fall prey to whim, sentiment, and chance, went unheeded in favor of the efficient market theory and rational expectancies. In the U.S., Akerlof and Shiller (2010), Kahneman (2011), and Camerer, Loewenstein, and Rabin (2004) have all embraced the post Keynesian world as behavioral economists. Behavioral economists espouse that a better understanding of psychology would improve theoretical insights as well as economic decisions (Camerer et al., 2004).

Researchers have branched off on a sub discipline of behavioral economics, which is behavioral finance. Behavioral finance models that incorporate psychological and sociological factors are often developed to explain market anomalies and investor behavior when rationale models do not provide a sufficient explanation (Muradoglu & Harvey, 2012). This study was an extension of the research into behavioral finance by forming what has been learned about investor behavior into a strategy for portfolio selection from which the individual investor might profit.

## STATEMENT OF THE PROBLEM

Price momentum (rapid acceleration in asset price) is based on the behavioral theory of positive reinforcement, whereby large increases in a stock's price draw in new investors and the inflow of new funds causes prices to rise further (De Bondt et al., 2008). As investors buy more, this action reinforces behavior and the stock price climbs, thereby creating a positive feedback loop (Harras & Sornette, 2011). Negative feedback loops occur as more investors sell their stocks causing the price to collapse. Price momentum strategies were noticed in 16 European markets to be successful predictors of profits (Metghalchi, Marcucci, & Chang, 2012). Evidence regarding Singapore, Malaysia, and Korea's futures markets indicated that price momentum strategies were able to predict profitability (Azizan et al., 2011). Additionally, such strategies were also demonstrated to be profitable in Canada (Assogbavi et al., 2011). Despite the success of price momentum research, most published researchers examined foreign markets that may not be as efficient as U.S. markets because of their size and lack of transparency (Chandra & Sharma, 2010; Lee & Andrada, 2011; Prorokowski, 2011; Sigano's 2010, 2012). Research in the United States has been conducted to benefit large investment companies and not the individual investor (Fox, 2009). A need exists to examine whether strategies based on behavioral finance theory could aid individual investors in providing a higher level of ROI than a strategy based on the efficient market theory in U.S. markets (De Bondt et al., 2008). Additionally, Peteros and Maleyeff (2013) asserted that a need exists to integrate behavioral finance into the education of individuals who make investment decisions. The focus of the study was on aiding individual investors through exploring new strategies based on behavioral finance theory instead of relying only on the efficient market theory.

## PURPOSE OF THE STUDY

The purpose of this quantitative quasi-experimental study was to compare the effectiveness of two different investment strategies with respect to return on investment (ROI). One investment strategy was based on behavioral finance theories of price momentum and compared to an equally valued investment strategy based on the efficient market theory. The goal of the research was to examine whether distinct investment strategies based on behavioral finance theory can produce greater profits than an investment strategy based on the efficient market theory. Specifically, the resulting ratio level data was used to compare the percentage change in the ROIs of the behavioral finance-based investment strategy with the percentage change in ROI of an investment strategy based on the DOW 30 index fund portfolio that served as a proxy for the efficient market theory. The portfolios were updated quarterly using data from Trade Station Securities, a large online brokerage firm and a member of the New York Stock Exchange, and then the data was entered into SPSS 21 for analysis (Norusis, 2008). The ANCOVA with a single covariate was used to compare and examine a control group portfolio and experimental group portfolios (Cook & Campbell, 1979). In addition, an interrupted time series with a nonequivalent no-treatment control group time series study was used. The portfolios that represented the experimental group was based on a behavioral finance theory strategy having a paper starting value of $500,000 with equal distribution among 10 different companies' stock. The efficient market theory portfolio proxy was the DOW 30. The Dow 30 represented the control group and had a paper starting value of $500,000 as well. The behavioral finance strategy evaluated in the study, capitalizes on anchoring bias, which is the act of basing a judgment on a familiar reference point (Silva, 2011). The behavioral finance strategy also capitalizes on confirmation bias, the tendency of people to interpret information in a way that supports their previous beliefs, and positive feedback trading, which occurs when one buys securities when the price is rising and sells securities when the price is falling (Sehgal & Tripathi, 2009). Liquid stocks were selected. The behavioral finance strategy portfolios (the experimental groups) utilized moving averages (MA). MAs are averages of asset prices that can be based on periods as short as a few days or as long as a few years. MAs are a type of technical indicator similar to a momentum indicator, but the formula for calculating the moving average varies (Kirkpatrick & Dahlquist, 2011). Price momentum trading rules outperformed a buy-and-hold strategy in European markets (Metghalchi et al., 2012). Similarly to Metghalchi et al., the momentum strategy employs the 50 period MA and the 20 period MA on monthly price charts in which a buy signal occurred when the line representing the shorter period MA crosses upwardly from below the line representing the higher period MA, thus indicating a positive change in momentum. The 50 period MA, often represented by a light blue line, and the 20 period MA, often represented by a yellow line, are commonly used among those who observe an asset's price behavior by using technical price charts. The percentage change in ROI of the DOW 30 paper portfolio, which served as a proxy for the efficient market theory (the control group), had a starting value of $500,000. Comparisons were made between the percentage changes in the ROIs of the behavioral finance strategy portfolios (experimental groups) with the percentage change in ROI of the DOW 30 index fund portfolio (control group). The dependent, continuous variable was the percentage change in ROI for the portfolios. Dividends and transaction costs were included in the ROI calculations.

## RESEARCH QUESTIONS

The following research question was used to compare the percentage change in the ROI over 1 year of a strategy based on the behavioral finance theory of price momentum and a strategy based on efficient market theory. The price momentum strategy was based on anchoring bias, confirmation bias, and positive and negative feedback trading. The efficient market theory proxy was the DOW 30 index fund. ANCOVA with a single covariate was used to compare the resulting ROI data of the control group based on the efficient market strategy portfolio and the experimental groups based on the behavioral finance strategy portfolio. Additionally, an interrupted time series with a nonequivalent no-treatment control group time series study was used.

**Q1.** To what extent, if any, is there a difference between the percentage change in ROI over 1 year of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) and an efficient market based strategy of buying and holding the DOW 30 index fund?

### Hypotheses

**H1$_0$.** There is no difference between the percentage change in ROI over 1 year of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) and an efficient market strategy of buying and holding the DOW 30 index fund.

**H1$_a$.** There is a difference between the percentage change in ROI over 1 year of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) and an efficient market based strategy of buying and holding the DOW 30 index fund.

## NATURE OF THE STUDY

The need exists to examine whether a strategy based on behavioral finance theory could aid individual investors better than a strategy based on the efficient market theory in U.S. markets (De Bondt et al., 2008). The nature of the study was to compare the effectiveness of two different investment strategies with respect to ROI. One investment strategy was based on behavioral finance theories of price momentum and compared to an equally valued investment strategy based on the efficient market theory. The goal of the research was to examine whether distinct investment strategies based on behavioral finance theory can produce greater profits than an investment strategy based on the efficient market theory. Specifically, the resulting ratio level data was used to compare the percentage change in the ROIs of the behavioral finance-based investment strategy, represented by the experimental portfolio's Basket 1 and Basket 2, with the percentage change in ROI of an investment strategy based on the DOW 30 index fund portfolio that served as a proxy for the efficient market theory. Up to 12 months may be the optimal length for a strategy to be effective (Cheuny, 2010), therefore, the first round study covered a year, however, a second year was added to examine if momentum slowed. A second round of study was added because the first round statistics were so robust.

In this research, a beginning portfolio value of $500,000 was assigned to each of the portfolios. The behavioral finance portfolio contained U.S. stocks. The portfolios were updated quarterly using data from Trade Station Securities and entered into SPSS 21.0 for analysis of the resulting ratio level data. The average ROI of each investing strategy and their resulting portfolios, DOW 30, Basket 1, and Basket 2, was analyzed. From the total value of each portfolio, transaction costs were deducted. Dividends, when generated, were accounted for as well. Using ANCOVA with a single covariate the percentage changes in the ROIs of each portfolio's investment strategies were compared (Cook & Campbell, 1979). A covariate is a variable (something that can be changed) that may predict the outcomes which are being examined. This study's covariate, (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) was a pretreatment that impacted the ROI of the momentum portfolios. This research is similar to that conducted in Canada by Assogbavi et al. (2011).

Additionally, an interrupted time series with a nonequivalent no-treatment control group time series study was used (Cook & Campbell, 1979). The design is shown below:

$O_1 \quad O_2 \quad O_3 \quad X \; O_4 \quad O_5 \quad O_6 \quad O_7 \quad O_8 \quad O_9$ behavioral finance portfolio (1)

$O_1 \quad O_2 \quad O_3 \qquad O_4 \quad O_5 \quad O_6 \quad O_7 \quad O_8 \quad O_9$ efficient market portfolio

$O_1 \quad O_2 \quad O_3 \quad X \; O_4 \quad O_5 \quad O_6 \quad O_7 \quad O_8 \quad O_9$ behavioral finance portfolio

The interruption, or intervention (X), is the act of purchasing for the paper portfolios a group of stocks with shorter period MAs crossing from the below longer period MAs. A pre intervention comparison of price performance, of the group of stocks with the shorter period MAs crossing from the below longer period MAs, was made with the price performance of the DOW 30 stocks, which was the control group proxy. A post intervention price performance analysis of the portfolios of stocks with crossing MAs was compared to the price performance of the control group (DOW 30) stocks. The nonequivalent-group design is one of the most frequently used designs because it is perhaps the most intuitively sensible designs available (Trochim & Donnelly, 2008).

## SIGNIFICANCE OF THE STUDY

American individual investors have lost trillions in wealth and now mistrust traditional brokerages, their representatives, and their products (Redhead, 2011). The individual investor's animal spirits or desire for risk has been damaged (Aklerlof & Shiller, 2010). Individuals acting alone with varying degrees of competence, lack strategies to ensure profitability (Chandra, 2009). Because individuals on their own lack strategies, an argument can be made that behavioral finance theory has the potential to create value for society and for individuals by aiding individuals with strategy development. The study showed how new developments in behavioral finance can be used to construct strategies that can aid the individual investor. Specifically, positive feedback, resulting from cognitive biases, can be visually interpreted from the use of the shorter period MAs crossing from the below longer period MAs on monthly stock price charts. The study is significant in that no fundamental analysis of the underlying company's financial data was used. The two experimental momentum portfolios were based on chart pattern recognition alone, which means that no knowledge of accounting and no ability to read financial statements was required.

## LITERATURE REVIEW

### Overview

Economist Keynes' (1964) statements regarding the nature of investing gave rise to the conceptual framework for market activity based, not on hard numbers, but on theories borrowed from psychology and sociology. Human decisions concerning the future of investments are based not on mathematical expectations, but on the innate urge to activity, "our rational selves choosing between the alternatives as best we are able, calculating where we can, but often falling back for our motive on whim or sentiment or chance" (Keynes, 1964, pp. 162-163).

Because Keynes' (1964) observation that investors use calculations where possible, but fall victim to emotions, impulses, and chance, went unheeded in favor of the efficient market theory, 5 decades later, researchers werepuzzled over similar behaviors. In the U.S., Akerlof and Shiller (2010), Kahneman (2011), and Camerer et al. (2004) have all embraced the post Keynesian world as behavioral economists. Behavioral economists espouse that a better understanding of psychology would improve theoretical insights as well as economic decisions (Camerer et al., 2004).

Researchers have branched off on a sub discipline of behavioral economics, which is behavioral finance. Behavioral finance models, that incorporate psychological and sociological factors, are often developed to explain market anomalies and investor behavior when rationale models do not provide a sufficient explanation (Muradoglu & Harvey, 2012). However, theorists are warned to use extreme caution when making assumptions or decisions about the behavior of individuals in financial markets based on findings from psychology (Glaser, Langer, & Weber, 2007).

The Nobel laureate for economics, Kahneman (2011), provided the reason for the need to proceed carefully. Humans have two systems of decision-making: System 1 and System 2. System 1 processes fast, almost automatic, definitive, reflexive, and nearly unconscious, but is also lazy and prefers using biases like the anchoring bias to make decisions. System 1 is responsible for much of the errors in judgment that humans make. By contrast, System 2 is self-disciplined, methodical, and in control and capable of overriding lazy System 1. System 2 is better at making decisions and thus makes few errors in judgment, but can miss the obvious (Kahneman, 2011).

In this new century, individual investors endure a chaotic environment and lack the decision-making skills needed to survive financially (Chandra, 2009; De Bondt et al., 2008). Now the milieu becomes ever more fast-paced due to advances in technology and provocative events. The current task was to augment the behavioral finance research and in so doing, aid the individual investor in making better financial decisions.

### Investment Mistrust

Investor scandals have typically received much attention (Redhead, 2011). For example, professional financial advisor Madoff led a $65 billion Ponzi scheme that stunned the public (Jackson, 2010). Forte stole $50 million from investors, and Piccoli embezzled $17 million from charities (Krantz & Gogoi, 2009). Investors were defrauded. Federal authorities charged Cosmo with a $380 million Ponzi scheme and Stanford with $8 billion in fraud for selling safe certificates of deposit, then placing the money in real estate and private equity (Lee, 2009).

Because of these largely publicized scandals, individuals lack confidence not only in their own abilities, but also in the professional financial community. Redhead (2011) examined the growing mistrust of investors toward the financial industry and the professionals that sell investments. Mistrust was related to all levels of financial engagement: investors were fearful of engaging with advisors on financial products and strategies, they mistrusted financial institutions that produced the financial products, and they mistrusted asset markets in which financial products were invested (Redhead, 2011). The individual investor’s animal spirits or desire for risk has been damaged (Aklerlof & Shiller, 2010).

A number of reasons for investor mistrust exist. For example, a conflict of interest can arise when financial advisors receive a commission to sell to customer’s products and securities that may not be suited to their needs, but that garner higher commissions (Redhead, 2011). This frequently ensuing conflict of interest creates mistrust. Vasile, Sebastian, and Radu (2011), while researching the root cause of the 2008 world-wide recession, concluded that the collapse of ethical behavior by many in the financial markets was the most important factor. Lending and underwriting standards declined because those who profited from creating these innovative financial products never expected to hold them in their own portfolios, but sell them and pass the risk to greedy and naive investors all over the world (Vasile et al., 2011). The rational and irrational reasons for mistrust of institutions and their products are numerous. Many mutual funds, which financial advisors favor, have not performed well for individuals (Redhead, 2011). Additionally, market bubbles and market crashes engender a perception of risk.

However, Victoravich’s (2010) research showed that financial education made a difference in individual investor’s perceptions. Financial education for investors would help bridge the distrust between investors, financial markets, financial advisors, and the products they represent (Redhead, 2011). Therefore, the focus of this research was to add to the body of knowledge employed to educate individual investors on the skill of strategic investment. To see from where this goal arises, the remaining literature review of current behavioral finance research consists of three theoretical areas: (a) heuristic theories, (b) psychological and emotion theories, and (c) education and practice theories. Heuristic theories and psychological and emotional theories are the parent theories of this study’s hypotheses. Education and practice theories support the need for this research.

**Heuristic Theories**

Because modern investors acting alone, and without competence, lack strategies to be profitable, the focus of this section is on behavioral finance based investment strategies (Chandra, 2009; De Bondt et al., 2008). For example, heuristic strategies provide insight into how individual investors might increase their ROI. A heuristic is a method of solving a problem that has no known reliable formula. Intertwined with the individual’s heuristic abilities are the individual’s emotions, psychology, and education that affect their decision-making. The challenges of new technologies also play a role in an individual’s aptitude for profitability.

With the creation of the Internet, the amount of timely information available to investors has increased exponentially (Agrrawal & Borgman, 2010). The massive amount of information that any investor may obtain quickly, anywhere in the world, is a factor in investor decision making. However, such overwhelming amounts of information create ambiguity and uncertainty for many individual investors (Agrrawal & Borgman, 2010; Rosillo, De la Fuente, & Burgos, 2013). Because the information may be overwhelming and add to the investor's state of confusion and mistrust, many individuals rely on heuristics to aid in their decision-making.

Based on the findings by Maditinos, Sevic, and Therious (2007), the various methods for decision-making used by investors at the turn of the 21st century in Greece indicated the perplexed state of the average individual investor. In Indiaindividual investors also suffered from confusion (Chandra, 2009). Individual investors in Spanish markets were confounded by confusion as well (Rosillo et al., 2013). How the psychological perplexities interface with decision-making by the individual investor has and will evolve with time. The research by Maditinos et al. (2007) revealed, in depth, the heuristics of individuals in a financial crisis as well as the more educated professionals.

Specifically, Maditinos et al. (2007) examined the common practices of individual and professional investors concerning stock analysis and selection as well as the relationships that occurred between how long the asset was going to be held and the techniques that professional and individual investors use for stock analysis and choice. The focus was on ascertaining the effect of the different techniques adopted by individual and professional investors regarding portfolio performance. The sample population was divided into six different groups. The first group consisted of official members of the Athens Stock Exchange, the second of mutual fund management companies, the third was portfolio investment, the fourth being listed companies, the fifth was brokers, and the sixth category included all individual investors. The first five categories were professionals, while the sixth category was nonprofessional Maditinos et al., 2007).

In the Greek markets, four different methods of analysis were employed: (a) fundamental analysis, (b) technical analysis, (c) portfolio analysis, and (d) other opinions (Maditinos et al., 2007). The respondents rated their use of each method on a 5-point Likert-type scale, where a rating of 5 equaled *always* and a rating of 1 equaled *not at all* (Maditinos et al., 2007). Additionally, the respondents gave their job titles and numbers of years of experience with investing. A typical chief executive reported that fundamental analysis was the most important factor in the selection of specific stocks or portfolios and that the movement of the developed foreign stock market played a very important part. However, the typical view of individual investors was different in this study as many individuals focused on trading and not on long-term investing. The nonprofessional individual investors tended to follow their instinct and experience, received stock market information from newspapers and the media, and focused their investment practices based on that information as well as on reports from foreign markets. The subset of 224 individual investors ranked what influenced their decision-making in the following order: instinct and experience, newspaper and media, foreign markets, government policy, noise in the market, fundamental analysis, technical analysis, both fundamental and technical analysis, and portfolio analysis (Maditinos et al., 2007). A typical response from an individual investor was he or she used fundamental and technical analysis because the newspapers used them; however, the investor did not believe that he or she grasped the concepts well (Maditinos et al., 2007).

For all groups, technical analysis and the reviewing of price and volume charts were used more often in the short-term, whereas fundamental analysis was used most often in long-term stock selection (Maditinos et al., 2007). A combination of fundamental and technical analysis ranked second as the most important approach long-term. An interviewee stated that accounting manipulations could apply easily to a single accounting period, but in the long-term, these manipulations are identifiable and the true condition of a corporation is uncovered. Another participant in the study stated that long-term aggregated accounting ratios give a better indication of the tactical position of a corporation, the group of competitors, or the industry sector (Maditinos et al., 2007).

A deeper analysis of the data compiled on investor's actions indicated that all groups ranked price-to-earnings ratio as a preferred fundamental, followed by earnings per share, net operating profits after taxes, and return on equity (Maditinos et al., 2007). Interestingly, Siganos (2012) noted that heuristic strategies based on price and earnings were profitable in the UK market as well. After Maditinos et al. (2007) interviewed participants, the researchers concluded that fundamental investors preferred traditional accounting measurements. In the technical analysis group, individuals preferred chart analysis. Those groups preferring technical indicators used price momentum indicators (Maditinos et al., 2007).

The final analysis of the data compiled by Maditinos et al. (2007) involved the periods before 1999, during the market's sharp correction of 1999, and after the market's sharp correction of 1999. After the financial crisis, investors became very cautious, preferring to invest where the brokers advised, in mutual funds, or with professional investment companies. One investor, who perhaps shifted from Kahneman's (2011) System 1 to System 2, noted that he no longer based his judgments solely on his own experience; he realized that financial newspapers and noise in the market were not very good indicators of price action and could lead to very bad forecasts (Maditinos et al., 2007). Prorokowski (2011), in a qualitative analysis in Poland and the UK, reported different results indicated that learning had evolved in the individual investor population.

The performances of the professional groups were based mostly on fundamental analysis and not on nonfinancial factors, and these groups believed they did well (Maditinos et al., 2007). Individual investors often based their strategies on instinct and experience, newspaper and media, and activity in the market, and they did poorly, suffering significant capital losses. Few investors relied on conventional portfolio analysis, such as diversification, although the efficient market theorists suggested that investors should diversify (Maditinos et al., 2007). This is significant because it may not be that a problem lies with the application of the efficient market theory, but with individual investors rejecting the theory of conventional portfolio analysis. The portfolios are diversified across industries as conventional portfolio analysis dictates. The Maditinos et al. (2007) study is important also because of the findings regarding the conditions of the individual investor and why his or her ROI is often negative. Behavioral financial theory advocates believe they could aid, through education, this type of investor (De Bondt et al., 2008).

Although individual investors at the turn of the 21st century performed poorly (Madintinos et al., 2007), the following research showed that individuals adapt (Prorokowski, 2011). Prorokowski (2011) investigated equity appraisal heuristics used by nonprofessional individual investors from the Central European emerging markets of Poland and the UK. The purpose was to examine if recent crisis-induced changes had affected investing strategies. Additionally, the predictive ability and usefulness of analytical tools used by nonprofessionals faced with unstable market conditions were tested. One hundred and seventeen nonprofessional Polish and 28 nonprofessional UK investors completed questionnaires. Of these individuals, 52 also participated in semi structured interviews lasting 40 to 60 minutes (Prorokowski, 2011).

Perhaps for the first time in the history of the markets of Central Europe, nonprofessional investors performed better than professional investors in 2010 (Prorokowski, 2011).

Nonprofessional investors in Poland relied mainly on technical analysis as a primary tool for evaluating equities. Except during the European economic crisis, individuals used fundamental analysis to distinguish nascent risks. Individuals reviewed financial statements, balance sheets, and cash flow statements, and sought expert advice. Apparently, nonprofessional investors methodically analyzed the Polish market (Prorokowski, 2011). This would demonstrate a shift to Kahneman's (2011) System 2 thinking. These investors learned how to use technical strategies, such as price momentum, with fundamental strategies to improve their ROI (Prorokowski, 2011). Bonenkamp, Homburg, and Kempf (2011) also discovered that combination strategies could predict profitability. This research involved the comparison of the percentage change in ROI of an efficient market strategy against the percentage change in ROIs of a price momentum strategy derived from behavioral finance theory to assess whether price momentum strategies could be useful for the American individual investor, thereby advancing theoretical development.

The extent to which small individual investors can take advantage of stock market anomalies in the UK was investigated by Siganos (2012). A small number of companies in the study were employed to define a portfolio strategy and the strategies were applied to both long and short positions. The several strategies tested were dividend to price, earnings to price, return to assets, price, asset growth, size, and overreaction. For a strategy to be included in the research, the required stock data had to be easily available, the methodology simple, and transaction costs minimal. Both listed and delisted UK companies from July 1988 to June 2009 were utilized. The findings indicated that only the fundamental earnings to price strategy had any net gains after transaction costs. This strategy involved buying companies with low earnings to price and selling short companies with high earnings to price. The price spread between what buyers bid and what sellers asked for the assets eroded profits in most other portfolios tested according to Siganos. In the study, the bid to ask spread problem was minimized by using stocks that were liquid.

## RESEARCH METHOD AND DESIGN

The goal of the research was to examine whether distinct investment strategies based on behavioral finance theory can produce greater profits than an investment strategy based on the efficient market theory. Specifically, the resulting ratio level data was used to compare the percentage change in the ROIs of the behavioral finance-based investment strategy with the percentage change in ROI of an investment strategy based on the DOW 30 index fund portfolio that served as a proxy for the efficient market theory. Up to 12 months may be the optimal length for a strategy to be effective, therefore, the study covered at least 1 year (Assogbovi et al, 2011; Cheuny, 2010).

The three major categories of research methods, (a) qualitative, (b) quantitative, and (c) mixed methods, have been used to investigate individual investment strategies (Asness et al., 2008; Bonenkamp et al., 2011). All three methods have also been employed successfully to examine the attributes of profitable individual investors (Metghalchi et al., 2012; Prorokowski, 2011; Siganos, 2012). However, a qualitative study would be limited to only a small number of investors and a mixed methods approach may take longer to execute due to its multiple components (Maditinos, 2007). By employing the quantitative approach, numbers allowed a precise analysis for this study.

A quantitative methodology was appropriate in order to address the research question of this study, as the intent was to evaluate by comparison via ANCOVA with a single covariate the portfolio groups derived from two different theories by using one control group based the efficient market theory and two experimental groups based behavioral finance theory. As stated, this study involved the use of portfolios or group of stock symbols chosen based on behavioral finance theory, which is price momentum as observed by crossing moving averages, and efficient market theory portfolio using the DOW 30 index fund as a proxy (Chiang et al., 2012). A covariate is a variable (something that can be changed) that may predict the outcomes which are being examined. The covariate (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) was a pretreatment that impacted the ROI of the momentum portfolios. The dependent variable was a ratio level data regarding the percentage change in the ROIs of the strategies compared over 1 year (Assogbovi et al, 2011; Cheuny, 2010).

The study involved examination of the two behavioral theory portfolios against the proxy efficient market portfolio over a year from February 2012 to February 2013. An extended analysis of the three groups was completed from February 2013 to 2014 to examine the longevity of the strategy. Additionally, a second round of testing was conducted to compare the two behavioral portfolios with different stock symbols to a proxy for the efficient market theory portfolio from April 2013 to April 2014. This defrayed some of the limitations and assumptions that may have affected the results and added to the consistency of the results. All data sets were compared using both ANCOVA and the time series analysis.

The objective of time series analysis was to identify the nature of the phenomenon that was represented by a series of observations and to forecast or predict future values of the time series variables. These objectives required the patterns of observed data to be identified and described. In order to best illustrate visually the differences between the portfolios, an interrupted time series with a nonequivalent no-treatment control group time series study was used (Cook & Campbell, 1979). The design is shown below:

$0_1 \quad 0_2 \quad 0_3 \quad X \; 0_4 \quad 0_5 \quad 0_6 \quad 0_7 \quad 0_8 \quad 0_9$ behavioral finance portfolio (1)

- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -

$0_1 \quad 0_2 \quad 0_3 \qquad 0_4 \quad 0_5 \quad 0_6 \quad 0_7 \quad 0_8 \quad 0_9$ efficient market portfolio

- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -

$0_1 \quad 0_2 \quad 0_3 \quad X \; 0_4 \quad 0_5 \quad 0_6 \quad 0_7 \quad 0_8 \quad 0_9$ behavioral finance portfolio

The interruption, or intervention (X) was the act of purchasing for the paper portfolio a group of stocks with shorter period MAs crossing from the below longer period MAs for the two momentum portfolios. A pre intervention comparison of price performance, of the groups of stocks with the shorter period MAs crossing from the below longer period MAs, were made with the price performance of the DOW 30 stocks, which was the control group proxy. A post intervention price performance analysis of the groups of stocks with crossing MAs were compared to the price performance of the control group (DOW 30) stocks. Quarterly closing prices were used to compare the time series analysis.

In this research, a beginning portfolio value of $500,000 was assigned to each of the strategies. Shares were whole and not partial, thus the values was close to, but not exactly $500,000. The difference was in cash such that each portfolio had a starting value of $500,000. The behavioral finance portfolio contained U.S. stocks. These U.S. exchanges had both large and mid-sized companies listed. The average market cap of each company was over 1 billion; the average trading volume was to be greater than 700,000 shares a day (O'Neil, 2004). The reasons for the restrictions were to insure that the stocks bid/ask spread was not so large that it affected profitability. For instance, if one goes to buy a stock and the asking price is $50.00, but the last bid was $45.00, the $5.00 spread is too wide to be economical. The narrower the spread, the less likely loss from slippage occurs. The portfolios were updated quarterly using data from Trade Station Securities and entered into SPSS 21.0 for analysis of the resulting ratio level data.

**Population**

The population for the momentum portfolio were chosen from NYSE and NASDAQ listed companies. There are 2,800 companies on the NYSE. The NASDAQ has 3,700. These companies cover the spectrum of commerce including banks, manufacturing, technology; and products, such as cars and food.

**Sample**

The momentum portfolios were comprised of stocks whose price trades between $10 and $200 and had market capitalizations of $1 billion. These stocks needed to meet the criteria of the covariate on the monthly chart in the 3 to 12 months preceding the purchase. The covariate was buying stocks, using monthly price charts, in which the line representing the 20 period MA has crossed, from the bottom of the chart upward, the line representing the 50 period MA. There were 10 companies in each of the two momentum portfolios. The sample size was limited for three reasons. The first was that the stocks had to meet the minimum capital requirements and trade volume. The second was that only approximately 20 stocks at any given time meet the covariate requirement and do not overlap significantly in industry classification. Third, this study was targeted at individual investors, who can only remember and track about 10 stocks at a time. The DOW 30 represented the efficient market portfolio.

No test for significance exists for three groups of unequal size, therefore, none was exercised. Additionally, there was no mean by which to do a power analysis or confidence test on a three-way comparison.

The data was collected from the charts of the online brokerage house of Trade Station Securities. The appendix contains a complete depiction of all the stock charts employed in this study. The average 401(k) account balance, for each worker 55 years old who has been with the same employer for 10 years, is approximately $250,000 (Fleck, 2013). Therefore, each portfolio had a starting worth of the value of one couple's retirement of $500,000. The size of the portfolios had relevance because this is a common value among small investors.

**Materials/Instruments**

All the data was collected from the charts of the online brokerage house of Trade Station Securities. Trade station is one of several reputable online brokerages with identical information. An Appendix is attached with depictions of the physical stock charts employed in this study. The software, SPSS 21, was used to perform the ANCOVA analysis.

**Results**

The stocks for the momentum strategy portfolio were selected and purchased on February 3, 2012. Whole shares were used with each of the 10 stocks having an approximate starting value of $50,000. The remainder was approximately $200 in cash. The list of ticker symbols in the first portfolio, Basket 1, were AMT, CAR, DDD, EFX, EQIX, MAT, REGN, STX, TMO, and VFC (see Appendix). Basket 2 symbols were NWL, WMB, TWX, LOW, VIAB, MPEL, BX, M, UA, and HON (see Appendix). Each of the stocks met the criteria concerning the crossing MAs as well as the liquidity requirements. The $INDU is the symbol for the DOW 30 index fund. $INDU had an approximate starting value of $499,999 with approximately $1,000 in cash. An interrupted time series with a nonequivalent no-treatment control group time series study was used (Cook & Campbell, 1979). The design is shown below where X represents the purchase of the 10 stocks, which met the criteria:

$0_1$ $0_2$ $0_3$ X $0_4$ $0_5$ $0_6$ $0_7$ $0_8$ $0_9$ behavioral finance portfolio (Basket 1) (1)

--------------------------------------------------------------------------------

$0_1$ $0_2$ $0_3$ $0_4$ $0_5$ $0_6$ $0_7$ $0_8$ $0_9$ efficient market portfolio (DOW 30)

--------------------------------------------------------------------------------

$0_1$ $0_2$ $0_3$ X $0_4$ $0_5$ $0_6$ $0_7$ $0_8$ $0_9$ behavioral finance portfolio (Basket 2)

All three portfolios were followed for a period of 1 year, from February 3, 2012 and sold on February 4, 2013. A second year was added to the study of these portfolios as well in order to asses if 1 year was the ideal as Cheuny (2010) proposed.

An analysis of variance (ANOVA) was conducted to examine whether there was significant difference between the groups (DOW, Basket 1, and Basket 2) in terms of ROI percentage change after 1 year. The descriptive statistics for ROI based on the grouping variable is presented in Table 1. As observed in Table 1, the control group DOW 30 had mean percentage change of 12.16% (*SD* = 15.97%), while Basket 1 had mean percentage change of 54.06% (*SD* = 50.24%) and Basket 2 had a mean percentage change in ROI of 31.35% (*SD* = 21.66%). This shows that a higher gain is observed for Basket 1 and Basket 2 as opposed to DOW 30 index fund.

There is a difference between the percentage change in ROI, over 1 year, of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA), and an efficient market based strategy of buying and holding the DOW 30 index fund. The three groups were followed for an additional year to see if the momentum strategy would slow or falter.

The following is the data for the percentage gained after 2 years. Not including Dividends and transaction costs, Basket 1 gained on average 107.06%, DOW 27.27% (actually using all 30 stocks) and Basket 2 gained 94.53%. Standard deviations were given for each as well. Below, the graph shows the performance of $INDU as the DOW, and each momentum stock portfolio's, Basket 1 and Basket 2 for both years (Figure 1).

Table 1
*Descriptive Statistics of ROI based on Groups*

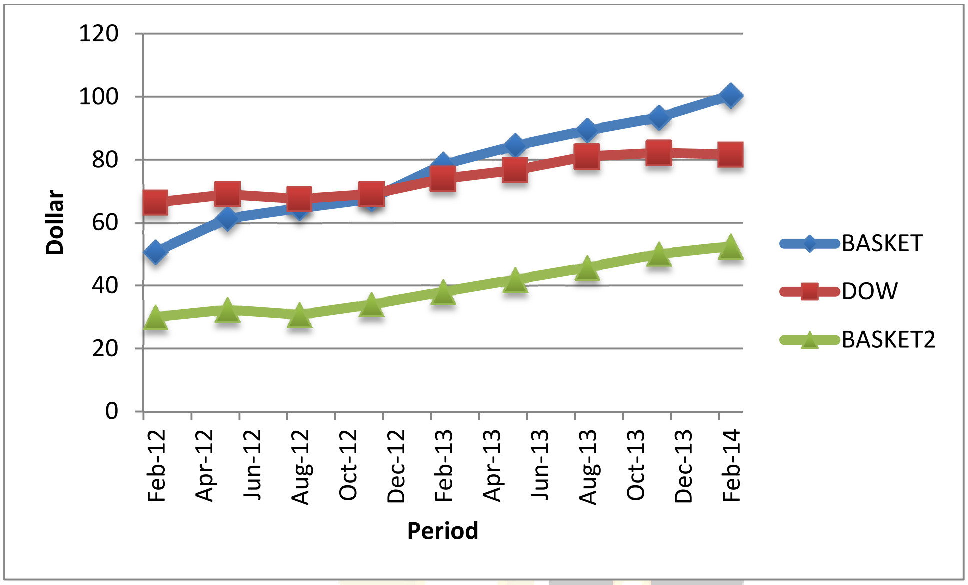


*Figure 1.* Time-Series Chart of Stock Prices from Feb 2012 to Feb 2014

The individual symbol price appreciations for Basket 1 are as follows for the year February 3, 2012 to February 4, 2013: AMT gained 20%, CAR gained 58.15%, DDD gained 179.6%, EFX gained 48.8%, EQIX gained 74%, MAT gained 21%, REGN gained 77%, STX gained 26.6%, TMO gained 31.7%, and VFC gained 10.6%. All stocks price appreciation exceeded the DOW 30 gain of 8.71%. In addition, the momentum portfolio also captured $13,677.36 in dividends, while only spending $140 in transaction costs. The first behavioral based portfolio resulted in a net ROI of 46.13%.

In Basket 2 the following are the individual symbols gains (not including dividends) from February 3, 2012 to February 4, 2013: BX gained 13.09%, HON gained 18.54%, LOW gained 43.52%, M gained 16,79%, MPEL gained 87.37%, NWL gained 26%, TWX gained 32.07%, UA 32.63%, VIAB gained 25.58%, and WMB 19.12%. Additionally, $16,433.04 accrued in dividends for the year, while only spending $140.00 in

| Group | Mean | Std. Deviation | N |
|---|---|---|---|
| Basket 1 | .5406 | .50245 | 10 |
| DOW 30 | .1216 | .15975 | 30 |
| Basket 2 | .3135 | .21667 | 10 |
| Total | .2438 | .31340 | 50 |

transaction costs with an online broker. The second behavioral portfolio, Basket 2, had a net ROI of 34.72% compared with the DOW 30 ($INDU) at 8.7% and the first behavioral portfolio, Basket 1, of 46.13%.

The literature indicated that a time horizon of 1 year was as long as expected for a momentum strategy to work (Cheuny, 2010). Looking over a 2-year period of February 3, 2012 to February 3, 2014, the proxy for the efficient market theory, the DOW 30 ($INDU) portfolio, had a net gain in ROI of 21.5%. Therefore, the original $500,000 increased to $607,733.86 for the DOW 30 over 2 years. However, the original $500,000 invested in the momentum portfolio Basket 1 increased to $1,160,236.72 when adding in dividends and transaction costs. Additionally, the original $500,000 invested in the momentum portfolio Basket 2 doubled to just over $1,000,000 when adding in dividends and transaction costs.

Figure 1 also indicates the time-series chart of stock prices from February 2012 to February 2014 based on groups of Basket 1, DOW, and Basket 2. Based on Figure 1, stock prices in the Basket groups had an increasing trend from 2012 to 2014. Meanwhile, DOW stock prices had been stable and rising from February 2012 to 2014.

Table 2 results for the percent change in stock prices from 2012 to 2013 as well as from 2013 to 2014. As observed from the results, there is significant change between 2012 and 2013 ($F$ = 7.826, $p$-value = .001). This indicated there was a significant difference between stock prices of companies in Basket 1, DOW, and Basket 2 for years 2012 to 2013. However, there was no significant difference observed in stock prices of these groups for the extended year 2013 to 2014 in Table 2. This could mean that the momentum portfolios began to slow or that the statistical significance of .406 was too high to be usable.

Table 2

*Test for Difference in Percentage Change in ROI based on Groups*

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Percent Change 2012 to 2013 | Between Groups | 1.202 | 2 | 0.601 | 7.826 | 0.001 |
| | Within Groups | 3.611 | 47 | 0.077 | | |
| | Total | 4.813 | 49 | | | |
| Percent Change 2013 to 2014 | Between Groups | 0.151 | 2 | 0.076 | 0.92 | 0.406 |
| | Within Groups | 3.858 | 47 | 0.082 | | |
| | Total | 4.009 | 49 | | | |

The literature indicated that a time horizon of 1 year was as long as expected for a momentum strategy to work (Cheuny, 2010). Table 2 shows that the data between the groups was not as significant in the second year 2013 to 2014 as the first year 2012 to 2014. That would indicate that the momentum strategies might lose their effectiveness after 1 year. However, looking over a 2-year period (February 3, 2012 to February 3, 2014) the proxy for the efficient market theory (DOW 30 portfolio) had a net gain in ROI of 21.5%. Therefore, the original $500,000 increased to $607,733.86 for the DOW 30 over 2 years. The behavioral finance theory as exemplified in the Basket 1 momentum portfolio for the period February 2012 to February

2014 had a net ROI of a profound 132%, which includes dividends ($27,354.72) and transaction costs ($140). Therefore, the original $500,000 invested in the momentum portfolio Basket 1 increased to $1,160,236.72. The individual symbol price appreciations in Basket 1(not including dividends) are as follows for the year February 3, 2012 to February 4, 2014: AMT gained 27.4%, CAR gained 167.68%, DDD gained 415%, EFX gained 76.84%, EQIX gained 49.59 %, MAT gained 18.64%, REGN gained 198.23%, STX gained 106.4%, TMO gained 104.6%, and VFC gained 74.8% (see Appendix for charts).

The second behavioral finance portfolio, Basket 2, for the same period of 2 years from February 3, 2012, to February 4, 2014, had a substantial increase in ROI as well. The total, including dividends of $32,866.08 and deducting for transaction costs, was up 101%. Here are the individual stocks gains in the second portfolio Basket 2 (not including dividends) from February 3, 2012 to February 4, 2014: BX gained 87.4%, HON gained 53.89%, LOW gained 70.72%, M gained 58.4%, MPEL gained 270.51%, NWL gained 64.43%. TWX gained 62.29%, UA 181.2%, VIAB gained 63.99%, and WMB 32.93% (see Appendix for charts). While the DOW 30 had gains of 21.5%, the behavioral finance portfolios, Basket 1 (gain 132%) and Basket 2 (101%), both doubled in 2 years.

Table 3

*ANCOVA of Percent Change of Stock Prices of 2012 to 2013 Data*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1.206a | 3 | 0.402 | 5.129 | 0.004 |
| Intercept | 1.197 | 1 | 1.197 | 15.271 | 0.000 |
| Buying Stock Price | 0.004 | 1 | 0.004 | 0.052 | 0.82 |
| Group | 1.206 | 2 | 0.603 | 7.693 | 0.001 |
| Error | 3.606 | 46 | 0.078 | | |
| Total | 7.784 | 50 | | | |
| Corrected Total | 4.813 | 49 | | | |

a R Squared = .251 (Adjusted R Squared = .202)

Table 3 shows the ANCOVA for 2012 to 2013 that support the alternative hypothesis having an $F$ of 5.129 and a significance $p$-value of .004. The results were exceptionally robust for the February 2012 to 2013. Thus, for consistency, a second round of testing was performed over a different period using different symbols for the two behavioral finance portfolios.

The DOW 30 ($INDU), the efficient market portfolio rose from April 5, 2013 to April 7, 2014. The $INDU went from $14,565.25 to $16,245.87. To meet the requirements of the $500,000 portfolio, 34 shares were purchased with the remaining $4,781.5 in cash. The efficient market proxy achieved an ROI of 11.54%.

Two new behavioral finance portfolios were constructed, which met the requirement that they be U.S. companies, have a capitalization of over $1,000,000, trade 700,000 shares a day trade between $10 and $150, and have a 20 period MA crossing from below a 50 period MA on the monthly period in the year before the purchase. The following randomly chosen two portfolios resulted. Basket1: DAL, ADBE, ALL, ATVI, CVS, ZION, GD, MAS, MGM, and GILD. Basket 2: ZMH, PWR, USB, VLO, YHOO, MON, MDT, FITB, TOL, and FRX (see Appendix).

Using the time interrupted series analysis along with the formula that was used to calculate equally weighed portfolios, the data showed both momentum portfolios had higher ROIs for the period of April 5, 2013 to April 7, 2014 than the efficient market theory portfolio (see Appendix Figures 24-43). The efficient market proxy started at $14,565.25 and climbed to $16,245.87 (see Appendix). A $500,000 portfolio allowed 34 full shares to be purchased with $4,781.50 in cash. The efficient market theory portfolio for the period had a return of 11.54%. The first April 2013 to April 2014, momentum portfolio, Basket 1, had an ROI, which includes dividends and transaction cost, of 52.9% for the year. The second momentum portfolio, Basket 2 had an ROI, which includes dividends and transaction cost of 42.1% for the year. The individual symbol's price appreciation for the first momentum portfolio, Basket 1, were as follows: GILD gained 46.75%, ALL gained 14.25%, ADBE gained 41.08%, CVS gained 34.44%, ATVI gained 37.14%, MAS gained 17.32%, MGM gained 99.5%, ZION gained 31.24%, GD gained 54.76%, and DAL gained 139.82% (see Appendix). The individual symbol's price appreciation for the second momentum portfolio, Basket 2, were that ZMH gained 30.7%, PWR gained 35.43%, USB gained 26.86% , VLO gained 29.51%, YHOO gained 46.39%, MON gained 9.03%, MDT gained 31.2%, FITB gained 41.06%, TOL gained 17%, and FRX gained 140.9% (see Appendix).

Descriptive statistics and an ANCOVA were performed as shown in Table 4. Additionally, ANCOVA was conducted to examine whether there is significant difference between the groups (DOW, Basket1, and Basket2) in terms of the percentage change in ROI after 1 year considering buying stocks as covariate. The descriptive statistics for ROI based on the grouping variable is presented in Table 4 and 5. As observed in Table 4, the control group DOW 30 has mean percentage change of .1655 while Basket 1 of .5163 has mean percentage change of and Basket 2 had a mean percentage change in ROI of .4081. This shows that a higher gain was observed for Basket 1 and Basket 2 as opposed to DOW 30 index fund, which also supports the alternative hypothesis.

Table 4

*Descriptive Statistics for April 2013 to 2014*

| | Mean | Std. Deviation | N |
|---|---|---|---|
| Basket 1 | .5163 | .39028 | 10 |
| Basket 2 | .4081 | .36778 | 10 |
| DOW 30 | .1655 | .16012 | 30 |
| Total | .2842 | .30125 | 50 |

Moreover, as observed from Figures 2, although the stock prices of DOW, which started out higher, were still higher, the ROI had decreased for DOW stocks from the third quarter to the selling time. On the other hand, it can be observed that the stock prices for Baskets 1 and 2 had significantly increased over the quarters. Note that the overall prices of DOW stocks were higher than the other two portfolios, but the DOW increased in percentage less over the year than the others.

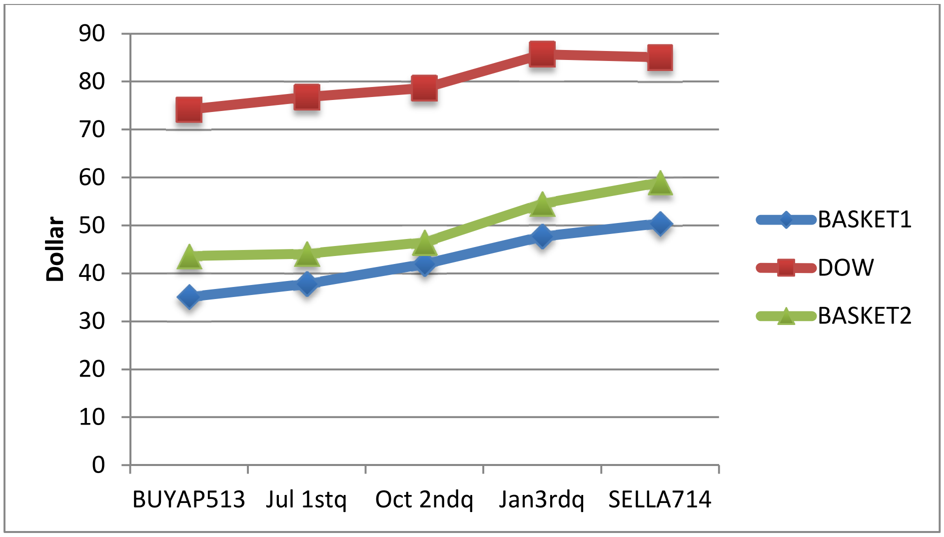


*Figure 2.* Time-Series Chart for Stock Prices based on Groups

The result of the ANCOVA presented in Table 4 support the alternative hypothesis. The analysis showed that the group variable significantly differentiates the percentage change in ROI after 1 year of investment ($F = 4.518$, $p = .016$). These results determined that a significant difference existed in the change in ROI for stocks based on the classifications of Basket 1, DOW, and Basket 2 while controlling for the buying price. The research showed that regardless of the buying price of a stock, the classification of Basket 1, DOW, and Basket 2 significantly affected the change in ROI over the year. The ANCOVA supported the alternative hypothesis posed in this study because the classification was based on being in the efficient market theory group or in one of the behavioral finance theory groups.

Table 5
*ANCOVA Test for Difference in Percentage Change in ROI based on Groups*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1.254a | 3 | 0.418 | 6.02 | 0.002 |
| Intercept | 2.902 | 1 | 2.902 | 41.812 | 0.000 |
| Buy Stock | 0.139 | 1 | 0.139 | 1.997 | 0.164 |
| Group | 0.627 | 2 | 0.314 | 4.518 | 0.016 |
| Error | 3.193 | 46 | 0.069 | | |
| Total | 8.484 | 50 | | | |
| Corrected Total | 4.447 | 49 | | | |

a R Squared = .282 (Adjusted R Squared = .235)

## EVALUATION OF FINDINGS

The results of the research were not expected. Conventional wisdom, most text on investing, and many successful investors encourage a primarily fundamental or mixed approach of both technical and fundamental analysis of stocks (Block& Hirt, 2008; Maditinos, 2007; O'Neil, 2004; Prorokowski, 2010; Victoravich, 2010). Very few suggest a completely technical approach to purchasing stocks (Metghalchi et al., 2008; Metghalchi et al., 2012).

The results of this study substantiates the hypothesis: There is a difference between the percentage change in ROI over 1 year of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) and an efficient market based strategy of buying and holding the DOW 30 index fund. In the first round of the study from February 2012 to February 2013, the second behavioral portfolio, Basket 2, had a net ROI of 34.72% compared with the DOW 30 ($INDU) at 8.7% and the first behavioral portfolio, Basket 1, of 46.13%. Extending the original round a second year the total for both years were. , the DOW 30 ($INDU) portfolio, had a net gain in ROI of 21.5%. Therefore, the original $500,000 increased to $607,733.86 for the DOW 30 over 2 years. However, the original $500,000 invested in the momentum portfolio Basket 1 increased to $1,160,236.72 when adding in dividends and transaction costs. Additionally, the original $500,000 invested in the momentum portfolio Basket 2 doubled to just over $1,000,000 when adding in dividends and transaction costs. Thus, while the DOW 30 had gains of 21.5%, the behavioral finance portfolios, Basket 1 (gain 132%) and Basket 2 (101%), both doubled in 2 years.

A second round of tests was conducted to rule out the possibility of luck. The DOW 30 ($INDU), the efficient market portfolio rose from April 5, 2013 to April 7, 2014. The $INDU went from $14,565.25 to $16,245.87. To meet the requirements of the $500,000 portfolio, 34 shares were purchased with the remaining $4,781.5 in cash. An ROI of 11.54% was achieved by the DOW 30. The first April 2013 to April 2014, momentum portfolio, Basket 1, had an ROI, which includes dividends and transaction cost, of 52.9% for the year. The second momentum portfolio, Basket 2 had an ROI, which includes dividends and transaction cost of 42.1% for the year (see Appendix for charts).

This researcher's intention was to augment the behavioral finance theory research and in so doing aid individuals in making better financial decisions. What the findings from the study mean is that behavioral finance theory can be used as a tool to shape heuristic strategies that can help individual investors maintain profitability. Additionally, the research indicates that pattern recognition could be a suitable basis for a profitable strategy.

## SUMMARY

The results of the analyses showed a large difference between the percentage change in ROI over 1 year of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) and an efficient market based strategy of buying and holding the DOW 30 index fund. In the first portfolio comparison from February 2012 to 2013, the results indicated that there is a significant difference based on the data gathered. The DOW 30 showed a mean percentage change of 16.55%, while Basket 1 had 51.63% and Basket 2 had 40.81% mean percentage change in ROI. A further analysis of the data determined that among stocks that gained, the second behavioral portfolio, Basket 2, had a net ROI of 34.72% compared with the efficient market theory portfolio, DOW 30 at 8.7% ,and the first behavioral portfolio, Basket 1 of 46.13%. The February 2012 study was extended out and a year was added to see if the momentum had slowed. The DOW 30 ROI was up 21.5% and both momentum baskets had doubled between February 2012 and 2014. The behavioral finance portfolios, Basket 1 gained 132%, and Basket 2 gained 101%.

The April 2013 to April 2014 also garnered robust statistics. All momentum portfolios tracked by time series analysis significantly outperformed the buy and hold efficient market proxy. The ROI for the efficient market, the DOW, was up 11.54%. The ROI for the momentum portfolio Basket 1 was up 52.9% and the ROI for the momentum portfolio Basket 2 was up 42.1%.

The results of both rounds of ANCOVA analysis indicated that not all groups were the same over the 1-year period. The analysis showed that the group variable significantly differentiates the percentage change in ROI after 1 year of investment ($F = 5.129$, $p = .004$; $F = 4.518$, $p = .016$). These ANCOVA's indicated that a significant difference in the change in ROI for stocks based on the classifications existed. However, the ANCOVA could not prove significance beyond 1 year. In conclusion, knowledge of behavioral finance could allow investors to form profitable strategies and should be encouraged in business schools and among individual investors.

## CONCLUSION

This research indicates support of the argument that behavioral finance theory has the potential to create value for society and for individuals by aiding individuals with strategy development. This study was an extension of the research into behavioral finance by forming what has been learned about investor behavior into a strategy for portfolio selection that the individual investor might profit from. The study showed how new developments in behavioral finance, which incorporate psychological and sociological factors, such as confirmation bias, anchoring bias, herding, positive feedback, and confidence, can be used to construct strategies that can aid the individual investor. The resulting momentum price strategy used for this study was utilized to resolve the research question: To what extent, if any, is there a difference between the percentage change in ROI over 1 year of a behavioral finance based strategy (buying stocks, using monthly price charts, in which the line representing 20 period MA has crossed, from the bottom of the chart upward, the line representing 50 period MA) and an efficient market based strategy of buying and holding the DOW 30 index fund? The researcher failed to reject the affirmative hypothesis through the use of modeling portfolios and testing them against the buy and hold efficient market proxy. The resulting ANCOVA data was statistically significant over the 1 year period for both rounds of tests. The momentum portfolios based on behavioral finance began to decline in statistical significance after 1 year. However, all experimental behavioral finance momentum portfolios tracked by time series analysis significantly outperformed the buy and hold efficient market proxy control portfolio. This study is significant because the momentum strategy tested did not rely on accounting or financial data but rather upon the recognition of patterns in price action that represent psychological and sociological factors such as herding, anchoring bias, confirmation bias, and positive feedback.

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