An Empirical Examination of the Behavioral CAPM

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Abstract

The fair value determination of financial assets has been always a debatable issue since the 1990s. It has always been questioned, whether this value depends, only on fundamentally calculated pricing models or it might be affected by other psychological and behavioral factors. The behavioral finance field addressed those issues extensively and provided alternative asset pricing models that incorporate and reflect behavioral aspects of decision-making. It addressed and explained the different heuristics and biases behind various market reactions that lacked any rational fundamental explanation. Behavioral finance is a relatively new paradigm that emerged to fill in the gaps in "Modern Finance". It did not develop specific models or strategies to beat the market; however, it has highlighted lots of challenging ideas that have promising directions of further research and analysis that may be very useful in welfare analysis and in wealth management.

In this paper, the author is introducing an empirical examination of some of these behavioral variables to the existing pricing models to enhance the predictability of the model. It also opens the door for further research and analysis in developing behavioral models.

JEL classification numbers: P33, P45
Keywords: CAPM, Behavior Finance, Asset pricing models.

1 ESLSCA Business School.

Article Info: Received: July 28, 2016. Revised: August 21, 2016. Published online: September 15, 2016.
1 Introduction

The Efficient Markets Hypothesis dominated the center stage of Finance Theory in the 1970’s. Anomalous evidence could not be fully accounted for by this hypothesis started showing up in 1980’s in the literature. During the same period, advancements been made in psychological theories, questioning the behavior of rational economic agents, but without necessarily applying them to investor behavior in financial markets. This, however, led to some literature attempting to explain anomalous evidence from a psychological viewpoint, but not in a formal way. In the 1990’s the development of financial economic models inspired by the psychology literature on behavioral biases and heuristics introduced the Behavioral Finance approach to the analysis of financial markets. In fact, the decade witnessed the development of a large body of behavioral finance literature. Looking into stock market crash in 1987, the internet bubble in 2000 and the financial crisis in 2008-2009, it is worth questioning the prices of these financial assets. Moreover, whether value is the same thing as price. On the one hand, we could assume that these assets have a fundamental value that can be derived through various models and techniques of valuations based on the expected future cash flow, and that this value determines the asset prices. On the other hand, we could simply assume that the value of an asset is nothing but the price at which it can be sold at any given point in time.

That investors react differently to company news is a popular justification for the deviation away from the efficient market hypothesis. Sometimes investors may over react to stocks’ performances where they may oversell stocks that have been realizing losses and overbuy those that have been performing well. With these reactions, those stocks will witness different prices compared to their fair values. The field of behavioral finance addressed these issues, provided alternative asset pricing models incorporating behavioral aspects of decision-making, and explained the different heuristics and biases behind these market reactions that lacked any fundamental explanation. Behavioral finance is a relatively new paradigm that emerged to fill in the gaps in "Modern Finance". This gap reflects the failure of modern finance in which behavior assumed to be derived only by standard rational behavior rather than the psychologically impacted error-prone human behavior. Statman (2010) pointed out that modern finance was built on the ground of rational behavior, and rests on four main building blocks. First, the "Mean- variance Portfolio Theory" of Markowitz (1952), second, the "Arbitrage Process" developed through the "Dividends Irrelevance proposition" of Miller and Modigliani (1961), third, the CAPM developed through the work of Sharpe (1964) and Lintner (1965 a and b), and finally, the "Efficient markets Hypothesis" of Fama (1970). He pointed out that these gaps or soft spots are related to the very basic building blocks of modern finance.
1.1 Definition of Key Terms:
- Behavioral Finance: A division of finance that uses psychology-based concepts to explain why investors often make irrational decisions and analyzes the anomalies that occur in the stock market.
- CAPM: A model that prices risky financial instruments by calculating the rate of return required by an investor to compensate for the level of risk taken.
- Efficient Market Hypothesis: An investment theory that states it is impossible to "beat the market" because stock market efficiency causes existing share prices to always incorporate and reflect all relevant information.
- Volatility Index: an index constructed using the implied volatilities of a wide range of S&P 500 index options. This volatility is meant to be forward looking and is calculated from both calls and puts
- Behavioral Biases: investors’ biases while trading different asset classes
- Market Index: An aggregate value produced by combining several stocks or other investment vehicles together and expressing their total values against a base value from a specific date. Market indexes intended to represent an entire stock market and thus track the market’s changes over time.
- Beta: is a measure of the volatility, or systematic risk, of a security or a portfolio in comparison to the market as a whole. Beta used in the capital asset pricing model (CAPM), a model that calculates the expected return of an asset based on its beta and expected market returns.
- Stock Volume: The number of shares or contracts traded in a security or an entire market during a given period. It is simply the amount of shares that trade from sellers to buyers as a measure of activity.
- Excess Return Alpha: This is often used to measure the investment manager’s ability to “beat the market” since it compares the excess return given by a security or portfolio over that of a benchmark with the same level of risk.
- Risk Free Rate: The theoretical rate of return of an investment with zero risk. The risk-free rate represents the interest an investor would expect from a risk-free investment over a specified period.
- Market Risk Premium: The difference between the expected return on a market portfolio and the risk-free rate.
- Bloomberg: A major global provider of 24-hour financial news and information including real-time and historic price data, financials data, trading news and analyst coverage, as well as general news and sports.

1.2 Statement of the Research Problem
The proposed study incorporates behavioral factors that complement the CAPM fundamental approach and develops a behavioral-based investment strategy driven...
by a set of variables derived from the literature on psychology and decision-making biases.
The idea behind the model is based on the assumption that any stock’s return at any given point in time cannot be fully explained by the extent of its systematic risk or beta. Accordingly, proxy variables for momentum effect and hindsight biases selected and tested. The proposed variables are as follows:
- Stock Volume
- Stock Volatility Index
- Market Volume
- Market Volatility Index

Addressing the return contribution of such factors adds a new dimension of understanding for the sources of returns and points to a potential development of fundamental-based active portfolio management strategies.

1.3 Objective of the Study
Behavioral finance models did not develop specific strategies to beat the market; however, it has highlighted lots of argumentative ideas that have promising directions of further research and analysis that may be very useful in public policy and welfare analysis, as well as in wealth management.

In this study, we are presenting some of these behavioral finance theories and how they tackle the psychological aspects in investors’ rational and irrational investment decisions. The study's main goal is to prove through quantitative measurements for few selected S&P500 stocks that behavioral regularities play a very important role in determining the value of these stocks over a four years period staring at 2011 until 2014.

This can be possibly achieved by using statistical techniques proving that there are other components that can be added to the CAPM equation. The stock’s volatility index, the stock’s traded volume together with the overall volume of the index that the stock is listed in (S&P500) and the Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX), a popular measure of the implied volatility of S&P 500 index options. The proposed modified equation is expected to have a positive impact on the financial model to have a better prediction for the stock's value and price.

1.4 Hypothesis Testing
This paper addressed the question of whether prices reflect fundamental values and whether deviations of prices from value could be explained solely by the efficient framework. Our review of the literature has shown that the Efficient Market Hypothesis (EMH) could not stand up to the empirical challenges to its semi-strong and strong market efficiency. Instead, we chose to explore the behavioral framework of analysis to market anomalies, adding a psychological dimension to finance.

In fact, the cognitive errors and emotional biases play a major role in the
investment decision-making process, resulting in irrational price performance and persistent mispricing that could not be fully accounted for by the efficient framework. Thus, the behavioral finance literature addressed the questions of why reality differs so much from the idealized world that underlies the efficient market and the Capital Asset Pricing Model and whether it could enable us to outperform the market. So far, behavioral finance models do not seem to have developed specific strategies to beat the market. Nevertheless, the field has promising directions of further research and analysis that may be very useful in public policy and welfare analysis, as well in wealth management.

Hence, this paper is addressing the question of whether investors’ behaviors variables addition to the CAPM equation, help us to better estimate the discount rate that will lead to a better estimation to stocks’ values and prices and consequently, can make better investment decision in order to maximize investors’ welfare.

\( H_0: \) There is no effect on adding proxy variables for behavioral biases on the model

\[ R_s - R_f = \beta (r_m - r_f) + \alpha X_1 + \Phi X_2 + \eta X_3 + \mu X_4 \]

Where:
- \( R_s \) is the stock’s weekly return
- \( R_f \) is the 10 year US T-bond
- \( r_m \) is the S&P500 market return
- \( \beta \) is the measure of the stock’s risk in relation to the market
- \( X_1 \) is the stock’s traded volume
- \( X_2 \) is the stock’s volatility index
- \( X_3 \) is the S&P500 traded Volume
- \( X_4 \) is the S&P500 Volatility index (VIX)
- \( \alpha \) is the coefficient of volatility index
- \( \Phi \) is the coefficient of S&P500 traded volume
- \( \eta \) is the coefficient of stock’s volatility index
- \( \mu \) is the coefficient of the stock’s traded volume

2 The Efficient Market Hypothesis

The Efficient Markets Hypothesis dominated the center stage of the Finance Theory in the 1970’s. The concept of the efficient market hypothesis (EMH) originated in the 10 years between 1955 and 1965 by economists Harry Markowitz and William F. Sharpe and continued to dominate the financial realm for the next 30 years. So first of all we need to have a closer look at the efficient market hypothesis and its origins.
The efficient markets hypothesis (EMH) maintains that market prices fully reflect all available information. Developed independently by Paul A. Samuelson and Eugene F. Fama in the 1960s, this idea has been applied extensively to theoretical models and empirical studies of financial securities prices, generating considerable controversy as well as fundamental insights into the price-discovery process.

The efficient market hypothesis’ theoretical framework is built on three important pillars:

1- Rational Investors are expected to value securities in a rational way.
2- Irrational investors will have random trades that will eventually cancel one another out without affecting the stock prices.
3- Irrational investors are expected to meet rational arbitrageurs in the market and they will eliminate their influences on prices.

With these basic foundations, it was generally believed that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. The accepted view was that when information arises, the news spreads very quickly and is incorporated into the prices of securities without delay.

Accordingly, two conclusions can be drawn from the empirical assumptions of the efficient market hypothesis, which are as follows:

1- The arrival of any new information, to the market, related to a specific security should result in the immediate correction of the value of that security, which is represented in its price.
2- Prices should not change without the arrival of new information about the value of a security.

Therefore, the efficient market hypothesis is divided into three different forms:

1- The weak form EMH: states that current security prices fully incorporate all historical information.
2- The semi-strong form EMH: states that current security prices should encompass all publicly available information, both current and historical.
3- The strong form EMH: states that current security prices incorporate all information, both public and private.

"The efficient market hypothesis is a consequence of equilibrium in competitive markets with fully rational investors" Shleifer 2000.

In his 1900 dissertation on "The Theory of Speculation,” Louis Bachelier searched for a formula which expresses the likelihood of a market fluctuation.” He ended up with a mathematical formula that describes the Brownian Motion.

In the finance world, Brownian Motion came to be called the random walk, once described as the path a drunk might follow at night in the light of a lamp post and that means the probability of a rise in price at any moment in time is the same as the probability of its fall. The clarification of Burton G. Malkiel in his article "The Efficient Market Hypothesis and Its Critics” stated that the logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow’s price change will reflect
only tomorrow’s news and will be independent of the price changes today. Nevertheless, news is by definition unpredictable and, thus, resulting price changes must be unpredictable and random. This means that all investors regardless of their experience in the stock market and their familiarity with trading of stocks and their prices, can base their decisions purely on the prices of the stocks provided by the market.

Malkiel also mentioned in his article that one of the first tests of the random walk hypothesis was developed by Cowles and Jones (1937), he made a comparison between the frequency of sequences, which are pairs of sequential returns sharing the same sign, and reversals in historical stock returns, which differ from the former in that they have opposite signs.

On the other hand, with a deviation from the random walk theory, Lo (1991) takes the long-term memory aspect into consideration. Time series with long-term memory show significant correlation when comparing between observations that took place in the past with those that may take place in the foreseen future, even if the time that has elapsed between them is long.

Departures from the random walk hypothesis can be fully explained by conventional models of short-term dependence. The estimation of the value of an investment is not, however, the only problem facing investors. Instead, they need to look at the overall level of risk exposure that holding different portfolios of several stocks entails an idea which Markowitz’s (1952) portfolio selection study gets at. His analysis of efficient portfolios, based on maximizing return for any given level of risk enables the identification of the efficient frontier, which is the trade-off between the expected return and risk. The personal profile of investors would then determine which point they would be on, on the efficient frontier. This implies that the ‘optimal portfolio’ is not the same across investors; because of the different utility functions they may have for risk exposure.

Sharpe (1964) and Lintner (1965) were responsible for the introduction of the Capital Asset Pricing Model (CAPM), a model that has since been frequently used in numerous studies pertaining to the field of corporate finance, despite the criticisms and arguments against it. However, in order to choose the optimal combination between the risk free asset and the market portfolio, investors must first be cognizant of the expected rate of return of the market as well as its standard deviation (Merton, 1980), since the return of the investment is magnified by taking the correct investment decision. Earlier studies have concluded that the “CAPM is a static model of portfolio allocation under uncertainty and risk aversion” (Mankiw & Shapiro, 1987, p. 6). Furthermore, the model illustrates a positive relationship between risk and return (Li, 1998; Lin, Wang, & Wu, 2011; Xing & Howe, 2003). According to the CAPM the expected rate of return is measured using the following formula:

\[ E(R_i) = R_f + \beta_i (E(R_m) - R_f) \]

Where \( E(R_i) \) is the expected return on the capital asset; \( R_f \) is the risk-free rate of
interest; \( \beta_i \) is a measure of systematic risk comparing the volatility of the security or portfolio to that of the market and \( E(Rm) \) is the expected return of the market. Graphically, the CAPM is represented by the Security Market Line (SML), which illustrates the relationship between the risk (\( \beta_i \), plotted on the x-axis) and the expected rate of return (\( E(Ri) \), plotted on the y-axis). On the graph, the market risk free rate (\( R_f \)) is represented by the y-intercept while the slope of the SML measures the market risk premium (\( E(Rm) - R_f \)). It has been empirically proven that a significant deviation from the expected relationship between beta and the market risk premium is seen when the two variables positively correlate. Moreover, these deviations are accompanied by extreme beta values on common stock (Jensen, 1972; Jensen & Scholes, 1972). Evidently, the expected rate of return of a common stock is substantially affected by its beta (Merton, 1980).

Another important aspect one should note is that a common stock’s expected rate of return is influenced by both controllable and uncontrollable risk factors. Fama (1970) draws on the implications of the CAPM and on the random character of the stock market in establishing the foundations for the Efficient Markets Hypothesis. According to this hypothesis, the equality of the risk-adjusted returns, derived from the CAPM equilibrium condition, implies that the market price is the best estimate of an asset’s fundamental value. This is because the market price reflects the expected future returns on an asset, after adjusting for the systematic risk that is captured by its level of covariance with the return on a portfolio that is representative of the market as a whole. This means that superior returns could not be extrapolated neither from looking at historical prices, nor at current ones (weak and semi-strong efficiency). This is because any new private and public information about expected returns get reflected in the asset prices when they come out. This makes it impossible to consistently achieve abnormal returns (strong form efficiency) because the changes in the prices are based on the changes in the available information, which evidently do not rely on historical information or on present information. Thus, stock prices may be looked at as following a random walk, represented by arbitrary changes in available information, just as Bachelier had suggested over a hundred years ago.

In fact, the theory argues that investors are rational and trade only based on changes in available information. In the case that irrational investors exist in the marketplace, their different trading strategies are likely to cancel out each other. Moreover, the rational investors would exploit any discrepancies caused by the irrational investors, so that the mispricing would not persist and there would be “no free lunches,” as prices get driven back to their fundamental values, so that eventually the CAPM equilibrium condition prevails. In fact, Friedman (1953) argues that the irrational investors are most likely to buy high and sell low, which means that eventually their wealth depletes and they disappear from the market, so that ‘in the long run market efficiency prevails because of competitive selection and arbitrage’ (Shleifer 2000).

In a recently published article "CAPM: an absurd model" the author, Pablo Fernandez (2014), in his critique to the CAPM model, stated that different
investors have different cash flow expectations and use different expected (and required) returns to equity (different expected market risk premium and different expected beta). One could only talk of the beta and the market risk premium if all investors had the same expectations. But investors do not have homogeneous expectations. He also affirmed that valuation is about expected cash flows and about required returns. We all admit that different investors may have different expected cash flows, but many of us affirm that the required return (discount rate) should be equal for everybody. That is the schizophrenic approach: to be a “democrat” for the expected cash flows but a “dictator” for the discount rate.

Shiller (1981) provides evidence of excessive stock prices’ volatility that could not be explained by efficient markets models such as the Dividend Discount model. The diagram below shows that the expected prices based on subsequent earnings follow a smooth trend whereas actual prices are highly volatile. This makes the case for the efficient markets weak, because the prices do not reflect the fundamental value of the stocks represented by their expected future earnings. He then argues that such evidence against the efficient markets is what gave rise to the behavioral finance discipline, which he defines as “finance from a broader social science perspective including psychology and sociology” (Shiller 2003). He summarizes the advances in behavioral finance through looking at the positive feedback models and the smart money models.

![Figure 1: Effect of earnings on price volatility](image)


The former is based on price speculation, which is what causes bubbles, as was the case with the tulip mania in the 17th century, when people started trading in tulips and making huge profits on the trade and then they began to believe that someone must lose his money in the end, making it a self-fulfilling prophecy that eventually made tulips worthless. This framework could be applied to other types of markets, such as the stock market and the housing market. In fact, the most recent internet
boom of the millennium and the housing boom that followed represent remarkable examples of the positive feedback framework, in which overexcitement about the prospect of positive returns from investments promote speculative trading and make future prices predictably positive. The latter is based on the assumption of the existence of two different groups in the market: noise traders, who distort market efficiency due to their irrational behavior and smart money traders who regulate market inefficiencies by exploiting arbitrage opportunities. Ritter (2003) stated that not all miss valuations are caused by psychological biases, however. Some are just due to temporary supply and demand imbalances and he emphasizes on that matter by the fact that when Yahoo was added to the S&P 500 in December 1999, index fund managers had to buy the stock even though it had a limited public float. This extra demand drove up the price by over 50% in a week and over 100% in a month. Eighteen months later, the stock price was down by over 90% from where it was shortly after being added to the S&P. These supply and demand phenomena might push stock prices far from their fair value in either direction.

Further contradictory evidence to the market efficiency theory shows on Ikenberry, Lakonishok and Vernaelen (1995) as they show that the market underreacts to open market share repurchases so that significant returns are not realized for buy-and-hold investors. They find that the market's initial reaction to the announcement stands at 3.5% on average, which is not much different than the average daily price standard deviation of most stocks. The empirical evidence thus implies that the strong/semi-strong forms of market efficiency are not manifested in share buybacks as we would have seen significant price surges following share buyback announcements (signaling theory) had the latter been true. This lends further evidence to investor behavior being psychologically impacted and not fully rational in the market efficient sense.

As previously mentioned, investors tend to react differently to new stock information, which justifies the deviations observed from the efficient market hypotheses. Sometimes investors may overreact to stocks’ performances where they may oversell stocks that have been realizing losses and overbuy those that have been performing well. With these reactions, those stocks will witness different prices compared to their fair values. This phenomenon is exhibited by price reversals, the idea that any increase in prices should ultimately be followed by a price decrease and vice versa.

Another aspect that should be examined when assessing the efficient market hypothesis, is the reaction of investors to earnings announcements that contain new information. According to a study conducted by Ball and Brown (1968), market prices usually incorporate up to 80% of the information content that is included in earnings ‘surprises’ before they are released. However, based on a more current paper by Bernard and Thomas (1990), there is a trend of investors occasionally underreacting to information related to future earnings based on current earnings releases.

This is mainly due to a puzzle dubbed “the post-earnings announcement drift’,
which was first introduced by Ball and Brown (1968), where it takes a number of days for market prices to fully reflect the information provided in the earnings announcement. Although such effects might prove contradictory to the efficient market hypothesis, their economic impact is frequently disputed. In frictionless markets they might, in fact, violate the efficient market hypotheses, however, the smallest hurdles such as taxes or trading costs can eradicate any profits gained from exploiting these inconsistencies.

3 The Behavioral Portfolio Theory

In contrast to the mean-variance portfolio theory, empirical evidence does not support that investors hold well diversified efficient portfolios. Merton (1987) provides a static asset pricing model with incomplete information. The main premise on which this model is based on is that a specific security, one that the investor is knowledgeable about, is used by the investor to form his optimal portfolio. The fact that investors only use familiar securities to build their portfolios, indicates a certain level of limited attention or preference for the familiar. If, however, investors based their portfolios on more complete information, this model would essentially boil down to the Sharpe-Lintner CAPM model. The difference here is that Merton’s model introduces certain frictions such as information costs and institutional structures. He concludes that the equilibrium expected returns are substantially affected by the flow of incomplete information among investors and that the effect of which is emphasized for smaller sized firms with little institutional following. Merton, however, believes that in the long run the efficient market equilibrium will be reached again. The structure of the model coupled with Merton’s emphasis on the information assumption shows that he is in fact defending the efficient market hypothesis by using the Behaviouralists’ arguments, as he modified the CAPM model by adding the incomplete information concept to it. Campbell (2001) found out when studying the U.S stocks; a clear tendency for correlations among individual stocks to decline over time. Correlations over five years of monthly data declined from 0.28 in the early 1960s to 0.08 in 1997. Statman (2010) pointed out that the current optimal diversification level, as prescribed by mean-variance optimizations should exceed 300 stocks, because at this level of diversification the benefits exceeds the costs. Yet, Goetzmann and Kumar (2001); in a study of more than 40,000 stock accounts at a brokerage firm found out that the mean number of stocks in a portfolio in the 1991-1996 period was 4 and the median number is 3. In the same vein, Polkovnichenko (2003) found also in a survey of 14 million households in 1998 that they were holding portfolios of 1 to 5 stocks. What is more, there is evidence that supports the concentration of portfolios in particular styles, such as large capitalization stock, or locations whether regional or national.
Shefrin and Statman (1999) developed behavioral portfolio theory as an alternative to the descriptive version of the Markowitz mean–variance portfolio. Mean–variance investors evaluate portfolios as a whole; they consider covariances between assets as they construct their portfolios. Mean–variance investors also have consistent attitudes toward risk; they are always averse to risk. Shefrin and Statman explain how BPT is consistent with the apparently irrational behavioral tendency of many people to purchase insurance policies and also buy lottery tickets. A BPT investor maximizes expected wealth subject to the constraint that the probability of wealth being less than some aspirational level cannot exceed some specific probability. The investor can tolerate failure to achieve at least the aspirational level of wealth but only with a small probability. In other words, the investor maximizes expected wealth on a particular portfolio subject to safety constraint.

This phenomena was clearly addressed in the Security, Potential and Aspiration (SPA) Theory by Lopez and Oden, it emphasizes that the decision maker when choosing among risky investment aims at maximizing security, potential and aspiration, yet in some situations the investor is willing to trade off some security and potential in exchange for high aspiration value. The decision maker who experience greater fear faces sharp reduction in security, where the investor with greater hope will have high probability of the occurrence of the favorable event. As a result hope is tied to the upside potential and the degree to which hope and fear are expressed in choices depends on the prospects offer of security and potential.

Accordingly, Behavioral investors build portfolios as pyramids of assets, layer by layer. The layers are associated with particular goals and particular attitudes toward risk. Some money is in the downside-protection layer, designed to avoid poverty; other money is in the upside-potential layer, designed for a shot at being rich.
Simon (1957) proposed the notion of bounded rationality, recognizing that people are not fully rational when making decisions and do not optimize but rather satisfice (satisfy and suffice) when arriving at a decision. Simon describes the phenomenon where people gather some not all available information, use heuristics to make the process of analyzing information and stop when they have arrived at a satisfactory decision and not necessarily the optimal one, that in contrast with the rational economic man making decisions according to the expected utility theory.

On the basis of his research in business organizations, Simon (1947) observes that when faced with a problem requiring a decision managers frequently do not have the resources (including time) to identify all possible courses of action, to evaluate each course of action against all relevant criteria, and to choose the best alternative for implementation. While rational, human beings only have a limited capacity to gather, store, process and understand.

Decision makers may choose to satisfice rather than optimize because the cost and time of finding optimal solution can be very high. People set constraints as to what will satisfy their needs. Simon refers to these constraints as aspiration levels. Kahneman and Tversky (1979) introduced the prospect theory as an alternative to the expected utility theory; it explains how individuals make choices between alternatives that involve risk and how they evaluate potential losses and gains. The findings emphasized that people tend to strongly prefer avoiding losses as opposed to achieving gains and that leads to a new behavioral understanding of investors that they are loss averse to a great extent as opposing to the original utility theory with all its developments that refers to investors are risk averse.

Prospect theory touches on only a subset of the issues raised in the behavioral finance literature. But its point of focus is a critical one: how individuals evaluate risky gambles or prospects and engage in risky choice behavior. Risky choice behavior is core to participation in financial markets. Some scholars argue that the value of prospect theory is its capacity to better explain the puzzles of human behavior in a world of uncertainty. These puzzles include the preference for certain outcomes (the Allias paradox); the unexpected (from a conventional theoretical perspective) high average rates of returns of stocks relative to bonds, referred to as the equity premium puzzle; overpaying for insurance and engaging in low expected value lotteries; individuals tending to weigh losses more than gains (referred to as loss aversion); the apparent overweighting of small errors (related to regret theory), which can result in individuals holding on to low-return assets for too long in the hope of a better tomorrow so as to avoid the regret of taking a loss; and the importance of reference points to decision making. The importance of reference points suggests and helps explain herding and cascades in investment behavior (Shiller, 1999; Fromlet, 2001; Zaleskiewicz, 2006). Prospect theory raises the question of whether individuals in financial markets are irrational as posited by mainstream behavioralists. If so, this irrationality suggests the need to develop policies to induce individuals to behave in a fashion consistent with the conventional wisdom’s specification of rational behavior. Such policies often
involve tricking people to behave in the desired manner or changing the attitude and preferences of the individual.

Prospect theory points to the possibility that individuals’ nonconventional behavior is intelligent and thus rational given the constraints facing the individual. Rational nonconventional behavior might be related to imperfect and asymmetric information and the rules of the game in financial markets. Such unconventional behavior might be consistent with economic efficiency. To such an extent, this suggests changing the constraints that decision makers face to correct the problem, as opposed to changing the behavior of individuals. This direction of behavioral economics is one not yet well traveled by behavioral finance scholars, but might lead to greater payoffs in terms of analysis and public policy than the irrationality perspective. Altering these constraints might be the most reasonable avenue both analytically and empirically. Behavioral finance conveniently allows for significant revisions of finance theory while maintaining important elements of the conventional core, which includes the assumptions that decision makers are intelligent in choice behavior. Smith (2005) makes a salient point with regard to the relationship between revealed choice behavior and the conventional wisdom. He finds that individuals tend not to behave in a manner consistent with conventional wisdom. Smith maintains that this is not a sign of irrationality in individual choice behavior or in suboptimal behavior. Nonconventional behavior can even result in superior economic results.

Loss aversion is an important concept that explains why investors deviate from expected utility. People do not just look at outcomes in absolute terms but instead tend to see them as gains and losses that are then compared to specific reference points. However, due to loss aversion, commensurate gains and losses are interpreted differently as people tend to be more sensitive to losses than to equal gains.

In an interview with Forbes magazine (Ackman, 2002), Kahneman elaborates on his interpretation of Bernoulli’s (1738) error and its relationship to choice behavior. He points out that Bernoulli, in his essay on decision making based on the Amsterdam spice trade, examined the outcome of a gamble and the utility of the outcome—introducing expected utility theory. The gamble consisted of investing in a ship and cargo that may or may not be lost at sea. There were substantial profits to be made if the ship succeeded in its venture and substantial losses if it failed. But Bernoulli looked at the utility of the state of wealth that followed from the outcome of the gamble which, Kahneman argues, is not how people think. Rather, individuals think in terms of gains and losses, irrespective of a person’s state of wealth. Bernoulli’s error consists of analyzing choice theory in terms of final states of wealth. According to Ackman (2002), Kahneman provides a contemporary example of this perspective: You have two people, both of whom get their quarterly returns on their stock portfolios. One of them learns his wealth has gone from $1 million to $1.2 million, and the other one learns his wealth has gone down from $4 million to $3.5 million. I can ask you two questions. I can ask you who is happier. There is no question the first one is happier than the second.
Then I can ask you who is better off financially. The second one is better off. Bernoulli’s analysis was in terms of who is better off financially—basically in terms of wealth. But when people think of the outcomes of their decisions, they think much more short term than that. They think in terms of gains and losses. That was the basic insight [of prospect theory]. As Ackman notes (2002, p. 1), Kahneman elaborates on this point: “When you think in terms of wealth—the final state—you tend to be much closer to risk neutral than when you think of gains and losses. That’s the fundamental way prospect theory departs from utility theory.” Moreover, Kahneman argues that thinking in terms of final states—the Bernoulli way—is more rational. It is more rational than behaving in terms of deviations from a reference point, which is how Kahneman finds individuals typically behave with regard to choice behavior.

Not only is loss aversion supported by evidence from a number of empirical studies (e.g. Kahneman et al. 1990; Tversky and Kahneman 1991; Barberis et al. 2001) it further explains a variety of field data (Camerer 2000). Important examples include the equity premium puzzle (Mehra and Prescott 1985; Benartzi and Thaler 1995).

McMahon (2005) stated that the chief attraction of prospect theory to BF scholars is its ability to accommodate heuristics and cognitive biases evidenced in real world decision-making that simply are not countenanced in expected utility theory.

Thaler and Johnson’s (1990) research stems from the same belief of the Prospect Theory that choices are not only influenced by their net effect on wealth, but rather by how they are perceived as gains or losses relative to a reference point. However, their results suggest an inverse S-shaped value function to that of the Prospect Theory. They find that, contrary to the Prospect Theory; prior losses make people more risk averse, especially when the second choice does not offer the opportunity to break even. Similarly, with prior gains, people become more risk seeking because of the House Money Effect, which implies that people will continue to take risks as long as they are losing the money they had gained and not their own money. This effect may diminish as the size of the potential loss approaches the initial stake. However, this effect is only observed with two-stage formulations of choices, whereas with the one-stage formulation, the prospect theory is at work. Also, when a choice following a loss offers the chance to break even, it is likely that people will manifest risk-seeking attitudes as is predicted by the Prospect theory and this effect is named the Break Even Effect.

The significance of loss aversion has been emphasized through several empirical studies. One of the ways in which loss aversion is clearly highlighted is in the discrepancy found in people’s perception of economic value. To obtain a certain good or service, people’s maximum willingness to pay (WTP) will often be different than their minimum willingness to accept (WTA) in exchange for selling the same good or service. Mean and Median WTP values are often found to be in the range of 1.4 to 16.5 times less that their corresponding WTA values (Kahneman
et al. 1990). While these concepts help analyze the degree of loss aversion, the substitution and income effects exemplify factors that distort this comparison, making it difficult to determine the degree of loss aversion. Loughran and Ritter (2002) tried to explain the severe underpricing of some IPOs in the article “Why Don’t Issuers Get Upset about Leaving Money on the Table in IPOs?”

![Image](image.png)

Figure 2: Loss aversion diagram
Source: Prospect Theory

If an IPO is underpriced, pre-issue stockholders are worse off because their wealth has been diluted. They argued that if an entrepreneur receives the good news that he or she is suddenly unexpectedly wealthy because of a higher than expected IPO price, the entrepreneur does not bargain as hard for an even higher offer price. This is because the person integrates the good news of a wealth increase with the bad news of excessive dilution. The individual is better off on net. Underwriters take advantage of this mental accounting and severely underprice these deals. It is these IPOs where the offer price has been raised (a little) that leave a lot of money on the table when the market price goes up a lot.

Kahneman and Tversky (1979) also argue that a preference for certainty allows individuals to be manipulated by frames (framing effects) that create the illusion of certainty, thereby generating choices that cannot be justified on grounds of SEU rationality. Both Smith (1985) and Altman (2004) contend that individuals can be fooled, but primarily in the short term. However, given brain construction, imperfect information, and uncertainty, one would expect (and experimental evidence suggests this to be the case) individuals to learn (adaptive expectations) what is and is not a cognitive illusion produced by a particular frame. Thereafter, individuals make choices based on their preferences that may include SEU rational preferences for certain events. Individuals also use positive or negative frames in their decision-making process. Kahneman and Tversky (1979) find that when events are framed positively, individuals tend to choose the certain event over the gamble even if the gamble yields an equal or greater expected value. They will also choose a positively framed gamble over a negatively framed one,
even when both yield the same expected value. This should not happen because the different frames have no substantive effect on events. Thus, individuals are subject to a perceptual or cognitive illusion. A lack of consensus exists around whether differential framing affects choice when prospects are substantively different. Gigerenzer (2007) argues that in a world of bounded rationality (the real world), rational individuals cannot be expected to use non-neoclassical heuristics to make their choices. Frames can signal information about the event, which is important in a world of imperfect information and uncertainty. When an event is positively or negatively framed, individuals read between the lines and attempt to extract surplus information from the frames. They read a positive frame as suggesting a better choice than the negatively framed event. This is a judgment call that might prove to be incorrect, but it is rational in a world of bounded rationality. Given these particular caveats, framing can affect the investment and disinvestment of financial assets. Different frames can yield different behaviors on the financial market. To the extent that frames distort the economic reality of financial assets, investment behavior can be inefficient.

As recently as three decades ago, human factors were rarely considered in theoretical and empirical research in finance (Miller, 1986). However, this has gradually changed, especially after the internet bubble at the beginning of the twenty-first century. As part of this new understanding of the importance of human factors, a new field of knowledge has gained prominence: Behavioral Finance, which uses ideas derived from psychology, many of which draw upon the seminal work of Daniel Kahneman, winner of the Nobel Prize in 2002. Behavioral Finance is a growing approach that sparks fertile and innovative field research in finance, with potential for development of new management tools, whether in the area of corporate finance or investments. Since the work of Kahneman (2002), the behavioral approach has provided results that are relevant for assessing the quality of executive decisions of Campeio (2012). In the area of asset pricing, in the last decade, for example, researchers have tried to discover and interpret anomalies in stock returns, such as reactions to news and extreme events (Bange 81 Miller, 2004; Hwang & Salmon, 2004). Thus, in April 2012, the Observatório da Inovação Financeira, a nucleus research of the Escola de Administração de Empresas de São Paulo, Fundação Getulio Vargas (FGV/EAESP), in partnership with researchers working in Brazil, the United States and Europe, and with the support of the Editorial Board of the RAE-Revista de Administração de Empresas, issued a call for papers devoted to modern issues in Behavioral Finance. From the methodological point of view, we understand that Behavioral Finance works on three levels: i) experiments with subjects under controlled laboratory conditions; ii) study of financial decisions in the real world, with applications in personal, family, professional and corporate spheres; and iii) the behavior of financial markets.
4 Limited Arbitrage Models: Smart Money and Positive Feedback

“Arbitrage is a double edged-blade: Just as rational investors arbitrage away inefficient pricing, foolish traders arbitrage away efficient pricing” Hirshleifer (2001).

The literature provides possible explanations for the empirical observations that prices do not always reflect the assets’ fundamental values, and so the efficiency condition is often violated in the marketplace.

These behavioral finance models employ the noise trader approach but do not go into psychological specifications of investor behavior. This approach allows for the existence of pseudo-information (false and fake) in the market, which may cause investors to trade for reasons unjustified by the actual information at a certain point in time. The idea was first advanced by Black (1986), who suggested that prices could be not only reflects the information of rational investors, but also the pseudo-information of noise traders. He also suggested that arbitrage could be limited because gains are not guaranteed.

This framework of analysis assumes that there are two types of traders in the marketplace: the noise traders and the arbitrageurs. The noise traders are the irrational traders who respond to pseudo-information and cause prices to deviate away from their fundamental values, thus distorting the market efficiency. The arbitrageurs are the market regulators who exploit the mispricing opportunities created by the noise traders and counter their effect, thus helping prices drive back to their fundamental values. However, in cases when it is in the interest of arbitrageurs to drive on the bandwagon along with the noise traders, rather than countering their behavior, they may behave sub-optimally and cause prices to deviate further away from their fundamental values. This framework provides a plausible explanation for the large trading volumes that form economic bubbles.

Ritter (2003) argued that there is no grantee that mispricing will be corrected with a reasonable time frame, Arbitragers that short the Japanese market in the late 1980 and the US market in 1990 lost huge losses before the prices adjusted after so many years. When trading against the noise traders, the arbitrageurs are faced with two types of risk; the fundamental risk that price deviations may reflect changes in information about expected future cash flows from a financial asset and the noise trader risk that the price deviations are caused by sub-optimal behavior of noise traders. However, in order to act against the mispricing, they need funds to engage in short-selling strategies, they need time because the mispricing might persist and they need to find substitute portfolios to buy the relatively cheap and sell the relatively expensive, so that the mispricing gets eliminated. These limitations pose restrictions on arbitrageurs’ actions. Thus, their demand for underpriced stocks will be limited, especially that the lending of financial assets is often conditional on liquidating positions within a certain time period, which may not be long enough for the arbitrageurs’ to realize the desired returns on their risk-
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In addition, risks are often entailed with selling overvalued stocks, because there are possibilities that their prices would rise further. Thus, the determination of the perfect timing of short selling is risky and difficult, which may prevent arbitrageurs’ reactions from driving prices all the way down to fundamentals. Also, in the case of stocks, it is unlikely for arbitrageurs to find close substitutes for mispriced assets and this implies the absence of a riskless hedge for arbitrageurs (Shleifer and Vishny 1997).

De Long, Shleifer, Summers and Waldmann (1990) argue that noise traders are likely to survive in the marketplace and not disappear as a result of losing their money from inefficient trading as had been argues by Friedman (1953). This is because their overconfidence or optimism might cause them to trade more aggressively, and take on more risks, which would then be rewarding. They are also less likely to learn from their mistakes because their strategies might be imitated, which then enlarges their overall effect on the market. Also, we know that new investors enter the market all the time and they are prone to the same behavioral biases that result in sub-optimal rationality as the preceding generations of investors. The model assumes the noise trader risk to be systematic across the market, because they are using models which Shefrin terms behavioral stochastic discount factor based asset pricing models. He concluded that investors do not make their decisions in an unbiased way. The stochastic discount factor to reflect this bias is a function of investor sentiment relative to fundamental value. The models focuses on market sentiment as a major determinant of asset pricing, which in turn is derived from systematic errors in judgment committed by investors. Shefrin asserts that sentiment causes asset prices to deviate from values determined using traditional finance approaches.

In order to have a tractable behavioral approach to asset pricing, it is necessary to have a well-defined measure of sentiment with an impact that can be traced on market prices and risk premiums. Shefrin (2005) proposes that the dispersion of analysts’ forecast serves as a proxy for the sentiment risk premium in the model. In support of this theory, he cites Ghysels and Juergens (2004) who determine that dispersion of analysts’ forecasts is statistically significant in a Fama-french multi-risk-factor framework. Alternatively, the dispersion of analysts’ forecasts may be a systematic risk factor not accounted for by other factors in the model. Doukas, Kim, and Pantzalis (2004) find that value stocks earn higher returns than growth stocks because the dispersion of analysts’ forecasts is greater for value stocks-which support dispersion of opinion as a measure for source of risk.

Shefrin develops a stochastic process for sentiment and a fundamental stochastic discount factor (SDF) based asset-pricing equation. The price of an asset is the expected value of its discounted payoffs. The discount rate captures the effects of the time value of money, fundamental risk, and sentiment risk. Sentiment pertains to erroneous, subjectively determined beliefs. If an investor’s subjective beliefs about the discount rate match those of traditional finance, the investor is said to have zero risk sentiment. If an investor’s subjective beliefs about the discount rate
do not match those of traditional finance, the investor’s beliefs are said to include risk sentiment. Thus, the discount rate on a security is the sum of the risk-free rate and fundamental premiums (reflecting sentiment-based risk). Although Shefrin cites evidence that investors commit errors that result in inefficient prices in the aggregate, it is important to determine if these errors are either systematic or essentially random in nature. If they are systematic, the errors may be predicted and exploited to earn excess returns. A logical assumption, in that case, is that rational and informed investors—however few in number—would act on these inefficiencies and thereby limit the scope of the pricing errors. If investors’ errors are random in nature, however, then observing and modeling them presents a formidable challenge, as indicated in the original work by Shefrin and Statman (1994).

5 Arbitrage Pricing Theory

The Arbitrage Pricing Theory (APT) was developed primarily by Ross (1976a, 1976b). It is a one-period model in which every investor believes that the stochastic properties of returns of capital assets are consistent with a factor structure. Ross argues that if equilibrium prices offer no arbitrage opportunities over static portfolios of the assets, then the expected returns on the assets are approximately linearly related to the factor loadings. (The factor loadings, or betas, are proportional to the returns’ covariances with the factors.)

Ross’ (1976a) heuristic argument for the theory is based on the preclusion of arbitrage. Ross formal proof shows that the linear pricing relation is a necessary condition for equilibrium in a market where agents maximize certain types of utility.

The APT is a substitute for the Capital Asset Pricing Model (CAPM) in that both assert a linear relation between assets’ expected returns and their covariance with other random variables. (In the CAPM, the covariance is with the market portfolio’s return.) The covariance is interpreted as a measure of risk that investors cannot avoid by diversification. The slope coefficient in the linear relation between the expected returns and the covariance is interpreted as a risk premium. Although the investor does not know future return realizations of his portfolio, the APT is a useful instrument for identifying common factors influencing portfolio returns. By estimating the sensitivities of a portfolio with respect to these common factors, the investor can reposition his portfolio in a way that leads to a more balanced risk exposure. For instance, a company can reduce its risk exposure to a factor that has a dominant effect on its overall costs of capital and, at the same time, can accept a higher exposure to a factor that has a negligible effect on the required investment return. By bearing a higher risk to the latter factor, the company can expect overall a higher stock return. Studies that have tested the APT empirically (Roll and Ross 1980; Reinganum 1981; and Chen 1983 among
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others) did not, however, always find positive risk premiums.

The APT is based on the insight that long-run asset returns are systematically influenced by unexpected shifts of certain factors such as the rate of inflation, the level of industrial production, or the slope of the yield curve. By estimating the sensitivities of a given portfolio to these factors, the investor can assess his or her current risk exposure. The APT can then be used to construct a portfolio with a desired exposure to these common factors by selecting assets with the appropriate risk exposure. A developer of business software will, for instance, have a relatively strong exposure to unexpected changes in economic activity in general and thus in industrial production but less exposure to inflation risk. By investing in companies that show a higher exposure to inflation risk and a lower exposure to the productivity factor, the software company can achieve the well-known diversification effect similar to the case of the CAPM.

A number of significant issues must be confronted when taking the APT from the theory outlined in the last section to its use in rate cases. The most important are:

(i) Is the APT a reasonable representation of security prices? Or stated conversely, can the APT be rejected statistically? (ii) Can the general economic factors which play the prominent role in the theory be identified? (iii) Do the general economic factors and their impacts on asset prices remain the same over time? Clearly, a negative answer to any of these questions will lead to difficulties in applying the APT in rate cases.

The preceding analysis suggests that the APT is a reasonable representation of asset prices—at least most tests do not reject it. It clearly has advocates as the best presently existing theory of asset prices. Bower, Bower and Logue [1984a] are both optimistic and cautious regarding APT. They state, most tests that have been reported are positive. APT, which explains variation in stock returns using several economy-wide variables, seems to perform better than the CAPM, which quantifies risk solely in terms of a single factor: beta, or co-variability with the market. Because APT promises to add to both our understanding of-and our ability to measure-risk, it is a model with a good chance of replacing CAPM as a practical tool of risk analysis for both investors and corporate planners. But before APT can be widely used by investors or corporate planners, the basic factors must be identified more precisely, single factor portfolios developed, and sensitivities to each factor continuously calculated and made easily available to users. Bower, Bower and Logue (1984).

With limited ability to determine the specific economic factors which generate security returns, the usefulness of APT in rate cases seems impaired. If the economic factors are unknown, how can the analyst estimate and apply APT in rate cases? Roll and Ross (1983) and Bower, Bower and Logue (1984) argue that APT can be applied despite the aforementioned difficulty and that it is superior in performance to the CAPM.
6 Alternative three factor Model

Fama and French (1992) find that size (ME) and book-to-market equity (B/M) contribute significantly to the explanation of the cross-section of average US returns provided by the market beta of the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). Building on this insight, they turn the two anomalies into common factors that provide a parsimonious description of US stock returns. The three-factor model of Fama and French (1993) consisting of the market portfolio and mimicking factor portfolios related to size (SMB) and book-to-market equity (HML) has become by now the standard model in asset pricing (Subrahmanyam (2010)).

The classic three-factor model of Fama and French (1993) is at large a reaction to the empirical shortcomings of the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) which has long shaped the way risk and return is evaluated by academics and practitioners. Though the one-factor model provides a theoretically elegant description of average returns, its empirical performance is fairly limited (see, e.g., the classic CAPM anomalies, Banz (1981), Basu (1983), DeBondt and Thaler (1985), Rosenberg et al. (1985), Bhandari (1988)). The Fama and French (1993) model delivers in empirical tests a better description of average returns than the CAPM. However, SMB and HML are merely the incorporation of the observed size and B/M anomalies into asset pricing factors due to their return predictive ability (see Fama and French (1992)). Therefore, SMB and HML lack an economic theory that governs the underlying asset pricing process (Barberis and Thaler, 2003). Though the model is ex-ante purely motivated from the data, two main economic interpretations of the Fama-French model can be distinguished in ex-post reflection: rational pricing and irrational pricing.

Although the choice of their factors appears rather ad hoc, Fama and French (1993, 1996a, 2011) advocate a rational pricing story arguing that SMB and HML represent compensations for risk in the context of a multi-factor version of Merton’s (1973) intertemporal capital asset pricing model (ICAPM) or Ross’s (1976) arbitrage pricing theory (APT). The set of explanatory portfolios in the classic three-factor model may span the superior (but not optimal) ex-ante mean-variance-efficient tangency portfolio relative to the one-factor model.3 In support of the rational pricing argument, Fama and French (1995) find that size (SMB) and book-to-market equity (HML) reflect firm fundamentals in earnings. In contrast to the risk-based interpretation, Lakonishok et al. (1994) suggest that the premium on HML does not arise from rational pricing as compensation for risk but is rather the result of mispricing in the sense that investors incorrectly extrapolate a firm’s past earnings behavior in the future. Moving down the same alley, Daniel and Titman (1997) document that it is the characteristics of small and value stocks rather than the factor loadings on SMB and HML which determine expected returns. However, this finding is not supported by Davis et al. (2000) in a longer sample period and therefore remains controversial.4 Thus, a sound
economic fundament of the Fama-French model is pending even after almost twenty years of intensive research. In their important work, Chen et al. (2010) propose a novel three-factor model capable of explaining several of the latest documented average-return anomalies (including momentum as the premier anomaly) which cause problems for the classic three-factor model. Their alternative factor model thus challenges the Fama-French model in asset pricing. Specifically, their model says that the expected return on a portfolio in excess of the risk-free rate is explained by the sensitivity of its return to three factors: the market excess return (MKT), the difference between the return on a portfolio of low investment-to-assets stocks and the return on a portfolio of high investment-to-assets stocks (DMI, disinvest minus invest), and the difference between the return on a portfolio of high earnings-to-assets stocks and the return on a portfolio of low earnings-to-assets stocks (PMU, profitable minus unprofitable). In analogous manner to Fama and French’s (1996a) approach then, Chen et al. (2010) confront their model with testing portfolios formed on a wide range of recent anomaly variables (beside the traditional size-B/M, e.g., momentum, accruals, net stock issues, and asset growth) and compare its performance with the Fama-French model. Since their model captures most of the recent average return anomalies left unexplained by the Fama-French model, they reject the classic model in favor of their alternative factor model.

A competing model of the three factor model of Fama and French is the model of the characteristics of the firm of Daniel and Titman (1997). Indeed, Daniel and Titman give a different interpretation for the relation between book to market ratio and stock returns. They reject the assumption of “factor of risk” in favor of the model of “the characteristics of the firm”: A low book to market ratio, which is one of the characteristics of the large firms, causes a low stock returns which does not, necessarily, correspond to a risk. Daniel and Titman (1997) reject the factor model for the U.S. stocks. However, Davis et al. (2000) show that this interpretation is specific to the period of study and confirm the results of the three factor model. In the same way, Lewellen (1999) confirms the superiority of the model of Fama and French (1993) compared to the model of Daniel and Titman (1997) in explaining time-varying expected returns on the U.S. market. Daniel et al. (2000) replicate the Daniel and Titman tests on a Japanese sample and fail to reject the characteristic model.

Berk et al. (1999) give a micro-economic model of the firm which integrate options of growth investments. The simulations of the model give consistent results with the conclusions of the three factor model. More recently, Ferguson and Shockley (2003) explain that the factor portfolios of Fama and French are correlated with a missing beta risk related to leverage. The empirical application of their model show that relative leverage and relative distress are powerful in explaining cross-sectional returns.
7 Description of research design

This study is based on data from S&P500 index covering selected stocks’ performances over a period of four years starting 2011 until 2014. The data used will include weekly prices for selected companies’ stocks, together with their volatility indices and weekly traded volumes. The data obtained for different stocks in diversified sectors and the data collected from Bloomberg. To keep things simple, the data used is the excess return of each stock on the last trading day of the week. In addition, for the sake of the study the volume and the volatility index of the S&P500 will be added to the model. The used risk free rate in the model will be the US 10 years Treasury bond over the same specified period.

\[
R_s = \beta(r_m - r_f) + R_f
\]

\[
R_s - R_f = \beta(r_m - r_f)
\]

\[
(R_s - R_f) = \beta(r_m - r_f) + \alpha X_1 + \Phi X_2 + \eta X_3 + \mu X_4
\]

\[
Y = \beta(r_m - r_f) + \alpha X_1 + \Phi X_2 + \eta X_3 + \mu X_4 + e
\]

Figure 4: CAPM modified equation to be tested

<table>
<thead>
<tr>
<th>Independent Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock’s traded volume</td>
</tr>
<tr>
<td>Volatility index of the Benchmark index</td>
</tr>
<tr>
<td>Stock’s volatility index</td>
</tr>
<tr>
<td>Market risk premium</td>
</tr>
<tr>
<td>Volume traded of the benchmark index</td>
</tr>
</tbody>
</table>

Figure 5: Variables
7.1 Procedures & Data Processing
The preliminary suggested methodology entails calculating the excess returns for the selected stocks from Bloomberg, as well as market indices for 4 years starting 2011 till 2014. The data gathered will be used to run several multiple regression models, the return lags under different period assumptions, the volume changes, and the market returns on the actual selected stock returns. The selected stocks were chosen based on the following criteria:
- Stocks are constituent of the S&P500 index with big market capitalization
- Stocks from different sectors to ensure generalization
- All stocks must have volatility index
- Selected stocks must have available data for the period 2011-2014.

The hypothesis will be tested by using Excel statistical model, to run a regression testing on the chosen data and check for the adjusted $R^2$. The $R^2$ is the coefficient of determination which is a statistical measure of how well the regression line approximates the real data points. Using this criterion, the higher the $R^2$ the higher the correlation between our variables, showing higher probability that behavioral finance (translated into our four suggested variables i.e. $x_1, x_2, x_3, x_4$) can be introduced to enhance the CAPM equation predictability.

The study will base its hypothesis testing with a confidence interval of 95%.

7.2 Purpose of the Study
The main aim of this study is to prove that investors’ behaviors have a noticeable effect on their investment decisions. Hence, the thought of modifying the CAPM famous equation that takes only into consideration two main variables in calculating required rate of return by investors’ on their alternative investments. Where the general idea behind CAPM is that investors need to be compensated in two ways: time value of money and risk.

$$R_s = \beta(r_m - r_f) + R_f$$

Therefore, by adding certain variables to be used as quantification to investors’ behaviors qualitative variables, will enhance the CAPM equation by making it more indicative and reliable in estimating the required rate of return. This study is based on data taken from the US stock exchange and specifically stocks listed on the S&P500. The choice of the S&P500 index is based on the fact that it is one of the most actively traded and reliable indices in the American stock market. The chosen stocks were from different sectors; this is to show that behavioral finance can be applied on all and any sector. The selection of the stocks was also based on the fact that they have a volatility index since 2011, the Chicago Board Options Exchange (CBOE) is the world's largest options exchange & the leader in...
product innovation, options education, & trading volume. The CBOE calculates and updates the values of more than 25 indexes designed to measure the expected volatility of different securities. These volatility indexes are key measures of market expectations of near-term volatility conveyed by listed option prices. Futures and options contracts now are available on some of these volatility indexes. The CBOE Volatility Index (VIX) is the world’s most widely followed barometer of investor sentiment and market volatility. The model we are presenting is based on weekly data collected historically from January 2011 until December 2014.

As shown in Table 1 are the selected stocks with their volatility indices used:

<table>
<thead>
<tr>
<th>Stock</th>
<th>Code</th>
<th>Volatility Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citi Group</td>
<td>C</td>
<td>CVOL</td>
</tr>
<tr>
<td>IBM</td>
<td>IBM</td>
<td>VXIBM</td>
</tr>
<tr>
<td>Google</td>
<td>GOOGL</td>
<td>VXGOOG</td>
</tr>
<tr>
<td>Goldman Sachs</td>
<td>GS</td>
<td>VXGS</td>
</tr>
<tr>
<td>Amazon</td>
<td>AMZN</td>
<td>VXAZN</td>
</tr>
<tr>
<td>Apple</td>
<td>AAPL</td>
<td>VXAPL</td>
</tr>
</tbody>
</table>

The study was done on each stock separately where a regression analysis was conducted, to see how by adding extra meaningful variables to the CAPM equation investors’ can enhance their expected return from each stock.

\[ R_s = \beta (r_m - r_f) + R_f \]  \hspace{1cm} (1)

This is the CAPM equation and for the sake of the study the \( R_f \) rate was taken to the left hand side of the equation and was considered to be the \( Y \) variable or the dependent variable in the new equation as follows;

\[ (R_s - R_f) = \beta (r_m - r_f) \]

\[ Y = \beta (r_m - r_f) \]  \hspace{1cm} (2)

As mentioned earlier, investors’ behavioral actions concerning their investments will be quantified in this study in four main variables that are mentioned below:

1- Stock’s traded volume \( X_1 \)
2- Stock’s volatility index \( X_2 \)
3- The benchmark index’s volatility index \( X_4 \)
4- The benchmark index’s traded volume \( X_3 \)
Therefore, this is how the modified CAPM equation that will be tested in this study looks like:

\[ Y = \beta (r_m - r_f) + \alpha X_1 + \Phi X_2 + \eta X_3 + \mu X_4 + e \]  

(3)

Where:
- \( R_s \) is the stock’s weekly return
- \( R_f \) is the 10 year US T-bond
- \( r_m \) is the S&P500 market return
- \( \beta \) is the measure of the stock’s risk in relation to the market
- \( X_1 \) is the S&P500 Volatility index (VIX)
- \( X_2 \) is the S&P500 traded Volume
- \( X_3 \) is the stock’s volatility index
- \( X_4 \) is the stock’s traded volume
- \( \alpha \) is the coefficient of volatility index
- \( \Phi \) is the coefficient of S&P500 traded volume
- \( \eta \) is the coefficient of stock’s volatility index
- \( \mu \) is the coefficient of the stock’s traded volume
- \( e \) is the random error, indicator of irrationality.

Market Risk Premium: \((r_m - r_f)\) this is the part in the CAPM that calculates the level of compensation needed by the investor in return for taking on more risk. Beta is the risk measure used to compare the returns given by the asset to those given by the market over time. In other words, it shows how much extra risk the investors are willing to accept over the expected market return.

The added variables are divided into two classes; one of them is directly related to the stock and its performance (stock’s traded volume and stock’s volatility index) and the other group is related to the index that this stock is listed in (the index traded volume and the index volatility index).

1- Investors always tend to trade in stocks that are listed in well-known and active indices like the S&P500 as they see that these stocks are trusted in the sense that they are included in such a big index which gives a sense of confidence in the stock regardless of the specific details of each stock on its own

2- Stock specific data: the data related to the stock itself; its volume and volatility index. After investors take the bigger picture, represented in the index, they start looking at each stock’s specific data. This will give them a clearer picture about the company apart from its fundamentals. This ensures for investors a higher expected return

The first added variable in the modified equation is the **Stock’s traded volume** \(X_1\). The stock’s traded volume is a very important indicator to how
investors’ observe the stock; the higher the volume the more confident investors’
are towards the stock.

This comes on the back that investors’ generally prefers to trade in liquid stocks.
Hence, the more the volume traded of a certain stock the more the new rational
investors’ will be willing to trade in it as they will observe it as a trusted stock by
many others beside them.

**Stock’s volatility index** $X_2$: For the sake of the study, the stocks were chosen
based on the fact that they have a volatility index. This is considered a limitation
to the study, as only six stocks were found that have a volatility index published
by the CBOE. Stock’s volatility index is a contrarian sentiment indicator that
helps determine when there is too much optimism or fear in the market. When the
sentiment reaches one extreme or the other, the market typically reverse course.
That is why we believe that volatility index is a very good quantification method
to investors’ behavioral trends and attitudes as it shows how the stock driven by
investors’ actions is volatile over a specific period.

The two other factors that is related to the index that each stock is listed in. the
first variable in this group is the **index’s traded volume** $X_3$. This variable shows
how confident investors’ are in the index itself as some investors start their trading
by picking the index and then seeing the stocks listed in it to decide whether to
invest in them or not. The benchmark index’s volume is the best indicator for such
a thing as it shows how active an index is unlike turnover, which is affected by
prices where volumes are, will give absolute figures of stocks.

What is applied on stock’s volatility index is applied on the **benchmark index’s
volatility index** $X_4$ as well where the volatility index will show how investors
observe market trends and their variability over time.

We treat the data of each stock separately while regressing the independent added
variables to the dependent variable $Y$. The procedures taken in the regression will
show the effect of adding extra variables to the CAPM equation and how this can
give better estimation to investors’ required rate of return after adjusting it to the
risk free rate. Six stocks were chosen based on the above-mentioned criteria and
their data were accessible and available for us to make use in the study.

8 **Data Analysis and Findings**

We started by regressing market risk premium $(r_m - r_f)$ on our new variable $Y$
which is the stock excess rate of return. As observed, the regression table gave the
following results for each stock:
1-  Citi group (C)

Table 2: Citi Group Regression Table, where X Variable 1 is the Market Risk Premium

It was observed that the R square and Adjusted R square for Citi group are 0.52 and 0.52 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model.

2-  Goldman Sachs (GS)

Table 3: Goldman Sachs Regression Table, where X Variable 1 is the Market Risk Premium
It was observed that the R square and Adjusted R square for Goldman Sachs are 0.68 and 0.68 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model.

3- Google (GOOGL)

Table 4: Google Regression Table, where X Variable 1 is the Market Risk Premium

It was observed that the R square and Adjusted R square for Google are 0.77 and 0.77 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model.

4- Apple (AAPL)

Table 4: Apple Regression Table, where X Variable 1 is the Market Risk Premium

It was observed that the R square and Adjusted R square for Apple are 0.63 and 0.62 respectively and, it is worth noting that statistically $R^2$ shows how data
points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model.

5- Amazon (AMZN)

Table 5: Amazon Regression Table, where X Variable 1 is the Market Risk Premium

<table>
<thead>
<tr>
<th>SUMMARY OUTPUT</th>
<th>Regression Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.766342039</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.58574843</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.583727693</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.037600968</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ANOVA</th>
<th>$df$</th>
<th>SS</th>
<th>MS</th>
<th>$F$</th>
<th>Significance F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
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<td>0.41091585</td>
<td>0.41091585</td>
<td>289.8683718</td>
<td>4.26367E-41</td>
</tr>
<tr>
<td>Residual</td>
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<td>0.290600901</td>
<td>0.001417595</td>
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<td></td>
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<tr>
<td>Total</td>
<td>206</td>
<td>0.701522751</td>
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</table>

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Standard Error</th>
<th>$t$ Stat</th>
<th>$P$-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
<th>Lower 95.0%</th>
<th>Upper 95.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4.43506E-05</td>
<td>-0.001543028</td>
<td>-0.28743244</td>
<td>0.97709825</td>
<td>0.00298027</td>
<td>0.000386729</td>
<td>0.000386729</td>
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<tr>
<td>X Variable 1</td>
<td>0.924794213</td>
<td>0.034369481</td>
<td>26.90742428</td>
<td>3.4024E-69</td>
<td>0.857031224</td>
<td>0.992557203</td>
<td>0.857031224</td>
</tr>
</tbody>
</table>

It was observed that the $R^2$ and Adjusted $R^2$ for Amazon are 0.59 and 0.58 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model.

6- IBM (IBM)

Table 6: IBM Regression Table, where X Variable 1 is the Market Risk Premium

<table>
<thead>
<tr>
<th>SUMMARY OUTPUT</th>
<th>Regression Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.882799449</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.779334868</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
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</tr>
<tr>
<td>Standard Error</td>
<td>0.022188794</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
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</table>

<table>
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<th>ANOVA</th>
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<th>SS</th>
<th>MS</th>
<th>$F$</th>
<th>Significance F</th>
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<td>Regression</td>
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<td>0.356460691</td>
<td>724.0094814</td>
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</table>

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<tr>
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<th>Standard Error</th>
<th>$t$ Stat</th>
<th>$P$-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
<th>Lower 95.0%</th>
<th>Upper 95.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4.43506E-05</td>
<td>-0.001543028</td>
<td>-0.28743244</td>
<td>0.97709825</td>
<td>0.00298027</td>
<td>0.000386729</td>
<td>0.000386729</td>
</tr>
<tr>
<td>X Variable 1</td>
<td>0.924794213</td>
<td>0.034369481</td>
<td>26.90742428</td>
<td>3.4024E-69</td>
<td>0.857031224</td>
<td>0.992557203</td>
<td>0.857031224</td>
</tr>
</tbody>
</table>
It was observed that the R square and Adjusted R square for IBM are 0.78 and 0.78 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model.

The market risk premium coefficients indicated strong positive effect with the excess return in the six stocks regression models.

The next phase of the study will focus on analyzing the addition of the four proposed behavioral independent variables to the market risk premium and observing $R^2$ and how it will change for each stock, by the addition of the new behavioral variables to the regression equation. It was observed that by adding the four variables the $R^2$ enhanced significantly in all stocks as presented below, the random error declined as well which is an indication in reducing behavioral biases, this all together indicates that these variables will improve the predictability of the model and this is clearly observed as follows:

1- Citi group (C)

Table 7: Citi Group modified Regression Table

<table>
<thead>
<tr>
<th>Regression Statistics</th>
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</thead>
<tbody>
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<td>Multiple R</td>
<td>0.799263256</td>
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<tr>
<td>R Square</td>
<td>0.638821753</td>
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</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.629837219</td>
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<tr>
<td>Standard Error</td>
<td>0.029053598</td>
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<tr>
<td>Observations</td>
<td>207</td>
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</tbody>
</table>

<table>
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<tr>
<th>ANOVA</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>Significance F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>5</td>
<td>0.300091713</td>
<td>0.060018343</td>
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<td>0.469758131</td>
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<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.005605635</td>
<td>0.0022206</td>
<td>-2.524379082</td>
<td>-0.0099843</td>
<td>-0.001227</td>
</tr>
<tr>
<td>Market Risk Premium</td>
<td>0.853574540</td>
<td>0.047796186</td>
<td>17.8566328</td>
<td>0.75932827</td>
<td>0.9478208</td>
</tr>
<tr>
<td>Stock Volume</td>
<td>0.015131253</td>
<td>0.007305314</td>
<td>2.071266705</td>
<td>0.039610882</td>
<td>-0.0072627</td>
</tr>
<tr>
<td>Stock Volatility Index</td>
<td>-0.164674744</td>
<td>-0.027155271</td>
<td>-6.064666066</td>
<td>-0.2182278</td>
<td>-0.1111278</td>
</tr>
<tr>
<td>S&amp;P 500 Volume</td>
<td>0.003987926</td>
<td>0.010934252</td>
<td>0.364718654</td>
<td>0.715704868</td>
<td>-0.0175726</td>
</tr>
<tr>
<td>S&amp;P 500 Volatility Index</td>
<td>0.054810954</td>
<td>0.025144185</td>
<td>2.179866042</td>
<td>0.030429336</td>
<td>0.10439118</td>
</tr>
</tbody>
</table>

It was observed that the R square and Adjusted R square for Citi group are 0.64 and 0.63 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. The coefficients indicate positive effect between the excess return and the market risk premium, stock volume, s&p500 volume and s&p500 volatility index and negative effect with the stock volatility index.
2- Goldman Sachs (GS)

Table 8: Goldman Sachs modified Regression Table

It was observed that the R square and Adjusted R square for Goldman Sachs are 0.71 and 0.71 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. The coefficients indicate positive effect between the excess return and the market risk premium, s&p500 volume and s&p500 volatility index and negative effect with the stock volatility index and stock volume.

3- Google (GOOGL)

Table 9: Google modified Regression Table

It was observed that the R square and Adjusted R square for Google are 0.81 and 0.80 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. The
coefficients indicate positive effect between the excess return and the market risk premium, s&p500 volume and s&p500 volatility index and negative effect with the stock volatility index and stock volume.

4- Apple (AAPL)

It was observed that the R square and Adjusted R square for Apple are 0.64 and 0.63 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. The coefficients indicate positive effect between the excess return and the market risk premium, s&p500 volatility index and stock volume and negative effect with the stock volatility index and s&p500 volume.

5- Amazon (AMZN)

It was observed that the R square and Adjusted R square for Amazon are 0.61 and 0.60 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of
adjusting the data for the number of data and variables in the tested model. The coefficients indicate positive effect between the excess return and the market risk premium and the stock volatility index and negative effect with stock volume, S&P500 volume and S&P500 volatility index.

6- IBM (IBM)

Table 12: IBM modified Regression Table

It was observed that the R square and Adjusted R square for IBM are 0.81 and 0.81 respectively and, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve: Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. The coefficients indicate positive effect between the excess return and the market risk premium and S&P500 volume and negative effect with the stock volatility index, stock volume and S&P500 volatility index. When we start having a closer look on the processed data from the regressing of the new added behavioral variables to the adjusted required rate of return we will see that all statistical numbers have improved, as shown in the below tables.

1- Citi group (C)

Table 13: Citi Group Change in Regression Statistics
It was observed that R Square and Adjusted R Square increased in Citi group stock after the addition of the behavioral factors from 0.52 to 0.64 and from 0.52 to 0.63 respectively, it is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. Moreover, adding more useful variables to the model increases adjusted $R^2$. On the other hand, standard error decreased in Citi group from 0.033 to 0.029, which indicates that adding the risk factors to the equation improved the representation of the model and confirms the significance of adding these variables to reduce behavioral biases.

2- Goldman Sachs (GS)

Table 14: Goldman Sachs Change in Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
<th>Regression Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.825588018</td>
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<td>R Square</td>
<td>0.681595576</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.680042384</td>
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<tr>
<td>Standard Error</td>
<td>0.026140813</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
</tr>
<tr>
<td>Multiple R</td>
<td>0.844015182</td>
</tr>
<tr>
<td>R Square</td>
<td>0.712361628</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.705206444</td>
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<tr>
<td>Standard Error</td>
<td>0.025091802</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
</tr>
</tbody>
</table>

It was observed that R Square and Adjusted R Square increased in Goldman Sachs stock after the addition of the behavioral factors from 0.68 to 0.71 and from 0.68 to 0.71 respectively. It is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. Moreover, adding more useful variables to the model increases adjusted $R^2$. On the other hand, standard error decreased in Goldman Sachs from 0.026 to 0.025, which indicates that adding the risk factors to the equation improved the representation of the model and confirms the significance of adding these variables to reduce behavioral biases.

3- Google (GOOG)

Table 15: Google Change in Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
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</thead>
<tbody>
<tr>
<td>Multiple R</td>
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<td>R Square</td>
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<td>Adjusted R Square</td>
<td>0.770956424</td>
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<tr>
<td>Standard Error</td>
<td>0.024590517</td>
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<tr>
<td>Observations</td>
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</tr>
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<td>Multiple R</td>
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<tr>
<td>R Square</td>
<td>0.806032246</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.801207177</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.022909149</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
</tr>
</tbody>
</table>
It was observed that R Square and Adjusted R Square increased in Google stock after the addition of the behavioral factors from 0.77 to 0.81 and from 0.77 to 0.80 respectively. It is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. Moreover, adding more useful variables to the model increases adjusted $R^2$. On the other hand, standard error decreased in Google stock from 0.025 to 0.023, which indicates that adding the risk factors to the equation improved the representation of the model and confirms the significance of adding these variables to reduce behavioral biases.

4- Apple (AAPL)

Table 16: Apple Change in Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
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</tr>
</thead>
<tbody>
<tr>
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<td>R Square</td>
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<td>Adjusted R Square</td>
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<tr>
<td>Standard Error</td>
<td>0.034630536</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
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</table>

It was observed that R Square and Adjusted R Square increased in Apple stock after the addition of the behavioral factors from 0.63 to 0.64 and from 0.62 to 0.63 respectively. It is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. Moreover, adding more useful variables to the model increases adjusted $R^2$. On the other hand, standard error decreased in Google stock from 0.035 to 0.034, which indicates that adding the risk factors to the equation improved the representation of the model and confirms the significance of adding these variables to reduce behavioral biases.

5- Amazon (AMZN)

Table 17: Amazon Change in Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
<th>Regression Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.765342035</td>
</tr>
<tr>
<td>R Square</td>
<td>0.58574843</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.583727691</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.037650958</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
</tr>
</tbody>
</table>
It was observed that R Square and Adjusted R Square increased in Amazon stock after the addition of the behavioral factors from 0.59 to 0.61 and from 0.58 to 0.60 respectively. It is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. Moreover, adding more useful variables to the model increases adjusted $R^2$. On the other hand, standard error decreased in Google stock from 0.038 to 0.037, which indicates that adding the risk factors to the equation improved the representation of the model and confirms the significance of adding these variables to reduce behavioral biases.

6- IBM (IBM)

Table 18: IBM Change in Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
<th>Regression Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.882799449</td>
</tr>
<tr>
<td>R Square</td>
<td>0.779334868</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.778258453</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.022188794</td>
</tr>
<tr>
<td>Observations</td>
<td>207</td>
</tr>
</tbody>
</table>

It was observed that R Square and Adjusted R Square increased in Google stock after the addition of the behavioral factors from 0.78 to 0.81 and from 0.78 to 0.80 respectively. It is worth noting that statistically $R^2$ shows how data points fits in a line or a curve; Adjusted $R^2$ also is the same with addition of adjusting the data for the number of data and variables in the tested model. Moreover, adding more useful variables to the model increases adjusted $R^2$. On the other hand, standard error decreased in Google stock from 0.022 to 0.021, which indicates that adding the risk factors to the equation improved the representation of the model and confirms the significance of adding these variables to reduce behavioral biases.

The findings of the six stocks changes in regression statistical analysis indicates and confirms that the addition of the proposed four independent variables have improved the R Square in all the six stocks indicating the significance of these variables in improving the model predictability and in reducing the behavioral biases.

9 Conclusion

Behavioral finance is a new field which aim to highlight and address how investors’ behaviors affected by each one’s psychological, social, and emotional
aspects, can affect their investments’ decisions combined with financial and economic factors taken into consideration.

The study aimed to explore the behavioral framework of analysis to by adding a psychological dimension to finance. In fact, the cognitive errors and emotional biases play a major role in the investment decision-making process, resulting in irrational price performance and persistent mispricing that might not be accounted for in the efficient framework. Thus, the behavioral finance literature addressed the questions of why reality differs so much from the idealized world that underlies the efficient market and the Capital Asset Pricing Model and whether it could enable us to outperform the market.

This study’s main goal was to show that this is possible by adding quantified variables representing investors’ behaviors to the CAPM equation to see its effect on determining the excess rate of return. By running statistical regression on those factors and their effect on the modified required rate of return.

The study and the analysis concluded that investors’ behavior might have an influence on their investment decisions, which will consequently have an effect on market prices and return. This has been observed by the empirical examination of the behavioral CAPM through introducing proxy variables for behavioral biases of individuals and running multiple regression analysis and identifying a major improvement in the random error, an indicator of irrationality.

The behavior finance field has promising directions of further research and analysis that may be very useful in public policy and welfare analysis, as well in wealth management. It might be worthwhile to develop new investment products geared towards behavioral investors and practically applying the behavioral portfolio theory in wealth management.

10 Limitations

There was a number of limitations to this study that includes the availability of volatility indices to different stocks in the market, since a larger sample of stocks would have led to a better representation of the study outcomes. The lack of market volatility indices in emerging markets would have also supported the study outcomes across developed and emerging markets.

11 Recommendations

The study opens the door for further research and analysis on the effect of behavioral finance variables and factors and how they can be added to current valuation models to enhance models predictability. It is recommended to study and compare outcomes in developed and emerging markets to assess whether behaviors biases impact on markets are similar or different.
Acknowledgments: This study was made possible through the help and support of many people. I would like gratefully to thank, Dr. Saad Metawa and Dr. Mohamed Elhennawi, for their assistance, support and valuable advices throughout the time I spent in writing this paper. I would also like to thank my family for their care, support and continuous encouragement, which made the product of this study paper possible.

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