



## 1.2 Statement of the Problem

Behavioral finance elicited a lot of interest from most researchers since literature in this field is still in its formative stages. A lot of research which have been conducted in this area focus on the implications of Behavioral finance and only a few focuses on how the dynamics of Behavioral finance affects professional investment practitioners. In fact none of the previous studies in this area address implications of the dynamics of behavioral finance using professional investment practitioners approach a gap that this study intend to fill.

## 1.3 Objectives of the Study

The general objective of the study is to identify the implications of the dynamics of Behavioral finance on Professional investment practitioners. The specific objectives are;

- To establish the implications of dynamics of behavioral finance on professional investment practitioners.
- To identify the effect of dynamics of behavioral finance on professional investment practitioners strategies.
- To establish the strategic responses to Global challenges in professional investment practitioners.

## 2. Literature Review

### 2.1 Theoretical Review

#### 2.1.1 Behavioral Portfolio Theory

*Behavioral portfolio theory*, introduced by Shefrin and Statman (2000), is a goal based theory. In that theory, investors divide their money into many mental account layers of a portfolio pyramid corresponding to goals such as having a secure retirement, paying for a college education, or being rich enough to hop on a cruise ship whenever they please. The road to behavioral portfolio theory started more than 60 years ago when Friedman and Savage (1948) noted that hope for riches and protection from poverty share roles in our behavior; people who buy lottery tickets often buy insurance policies as well. So, people are risk-seeking enough to buy lottery tickets while they are risk-averse enough to buy insurance. Four years later, Markowitz wrote two papers that reflect two very different views of behavior.

In one (Markowitz 1952a), he created mean-variance theory, based on expected utility theory; in the other (Markowitz 1952b), he extended Friedman and Savage's insurance-lottery framework. People in mean-variance theory, unlike people in the insurance-lottery framework, never buy lottery tickets; they are always risk averse, never risk seeking. Friedman and Savage (1948) observed that people buy lottery tickets because they aspire to reach higher social classes, whereas they buy insurance as protection against falling into lower social classes. Markowitz (1952b) clarified the observation of Friedman and Savage by noting that people aspire to move up from their current social class or "customary wealth." So, people with \$10,000 might accept lottery-like odds in the hope of winning \$1 million, and people with \$1 million might accept lottery-like odds in the hope of winning \$100 million. Kahneman and Tversky

(1979) extended the work of Markowitz (1952b) into prospect theory. Prospect theory describes the behavior of people who accept lottery-like odds when they are below their levels of aspiration but reject such odds when they are above their levels of aspiration.

A central feature in behavioral portfolio theory is the observation that investors view their portfolios not as a whole, as prescribed by mean-variance portfolio theory, but as distinct mental account layers in a pyramid of assets, where mental account layers are associated with particular goals and where attitudes toward risk vary across layers. One mental account layer might be a "downside protection" layer, designed to protect investors from being poor. Another might be an "upside potential" layer, designed to give investors a chance at being rich. Investors might behave as if they hate risk in the downside protection layer, while they behave as if they love risk in the upside potential layer. These are normal, familiar investors, investors who are animated by aspirations, not attitudes toward risk.

In 2002, *Wall Street Journal* writer Mylene Mangalindan told the story of David Callisch, a man who bet on one stock. When Callisch joined Altheon WebSystems, Inc., in 1997, he asked his wife "to give him four years and they would score big," and his "bet seemed to pay off when Altheon went public." By 2000, Callisch's Altheon shares were worth \$10 million. "He remembers making plans to retire, to go back to school, to spend more time with his three sons. His relatives, his colleagues, and his broker all told him to diversify his holdings. He didn't." Unfortunately, Callisch's lottery ticket turned out to be a loser. Callisch's aspirations are common, shared by the many who gamble on individual stocks and lottery tickets. Most lose, but some win. One lottery winner, a clerk in the New York subway system, said "I was able to retire from my job after 31 years. My wife was able to quit her job and stay home to raise our daughter. We are able to travel whenever we want to. We were able to buy a co-op, which before we could not afford." Investors such as Mr. Callisch and lottery buyers such as the New York subway clerk aspire to retire, buy houses, travel, and spend time with their children. They buy bonds in the hope of protection from poverty, stock mutual funds in the hope of moderate riches, and individual stocks and lottery tickets in the hope of great riches.

Mean-variance portfolio theory and behavioral portfolio theory were combined recently as mental accounting portfolio theory by Das, Markowitz, Scheid, and Statman (2010). Investors begin by allocating their wealth across goals into mental account layers, say 70 percent to retirement income, 20 percent to college funds, and 10 percent to being rich enough to hop on a cruise ship whenever they please. Next, investors specify the desired probability of reaching the threshold of each goal, say 99 percent for retirement income, 60 percent for college funds, and 20 percent for getting rich. Each mental account is now optimized as a sub-portfolio by the rules of mean-variance theory, and each feasible goal is achieved with a combination of assets. For example, the retirement goal is likely to be achieved in a sub-portfolio with a combination weighted toward bonds, the college goal is likely to be achieved in a sub-portfolio with a balanced combination of

stocks and bonds, and the getting rich goal is likely to be achieved in a sub-portfolio with a combination weighted toward stocks, perhaps with some options and lottery tickets thrown in. The overall portfolio is the sum of the mental account sub-portfolios, and it, like the mental account sub-portfolios, lies on the mean-variance efficient frontier.

### 2.1.2 Elegant Theories and Testable Hypotheses

The statement that behavioral finance is an interesting collection of stories but does not offer the equivalent of the comprehensive theory and rigorous tests of standard finance is as common as it is wrong. When people think about standard finance, they usually think about the CAPM and mean-variance portfolio theory. These two models are elegant, but few use them in their elegant form.

The elegant CAPM has been replaced as standard finance's asset pricing model by the messy three-factor model, which claims that expected return is a function of equity market capitalization and the ratio of book value to market value in addition to beta. In turn, the three-factor model has become the four-factor model with the addition of momentum and the five-factor model with the addition of liquidity. The list is likely to grow.

Similarly, few apply mean-variance theory or its optimizer in their elegant forms. Instead, it is mostly constraints on the optimizer that determine mean-variance optimal portfolios, and these constraints are often rooted in behavioral consideration. A constraint on the proportion allocated to foreign stocks is one example, driven by "home bias." But we don't need elegant models; we need models that describe real people in real markets. These are the models of behavioral finance.

Behavioral finance offers behavioral asset pricing theory and behavioral portfolio theory, which are no less elegant than the models of standard finance and are much closer to reality. Moreover, behavioral finance offers testable hypotheses and empirical assessments that can reject these hypotheses if they deserve to be rejected. For example, Shefrin and Statman (1985) offered the testable "disposition" hypothesis that investors are disposed to hold on to losing stocks. This hypothesis can be rejected by empirical evidence that investors are quick to realize losses. But the evidence among many types of investors in many countries supports the hypothesis.

## 2.2 Empirical Review

The asset pricing model of standard finance is moving away from the *capital asset pricing model* (CAPM)—in which beta is the only characteristic that determines expected stock returns—toward a model that is similar to the BAPM. For instance, the *three-factor model* formulated by Fama and French (1992), popular in standard finance, adds market capitalization and book-to-market ratio to beta as characteristics that affect expected returns. One difference between this three-factor model of standard finance and the BAPM is in the interpretation of these characteristics.

In standard finance, market capitalization and book-to-market ratios are interpreted as measures of risk; small-cap

stocks and stocks with high book-to-market ratios (value stocks) are considered high risk stocks, and the high risk justifies high expected returns. In contrast, in *behavioral asset pricing theory*, the same characteristics are interpreted as reflections of affect, an emotion, and representativeness, a cognitive bias. Both lead investors to identify good stocks as stocks of good companies. Small-cap stocks and stocks with high book-to-market ratios (value stocks) are stocks of "bad" companies (e.g., bank stocks in 2008).

These companies have negative effect, so investors shun them, depressing their prices and pushing up their expected returns. Statman, Fisher, and Anginer (2008) find that respondents in the *Fortune* surveys of admired companies consider stocks of small-cap, high book-to-market companies as unattractive investments, yet stocks of admired companies yielded lower returns, on average, than stocks of spurned companies.

Still, the road from the preferences of normal investors to security returns is not straightforward, as explained by Shefrin and Statman (1994) and more recently by Pontiff (2006). Suppose that most investors are indeed normal investors who believe, erroneously, that good stocks are stocks of good companies. But surely not all investors commit that error. Some investors are rational, investors aware of the biases of normal investors and seeking to capitalize on them favoring stocks of "bad" companies. Would rational investors not nullify any effect of normal investors on security prices through arbitrage? If the effects of normal investors on stock returns are nullified, risk-adjusted expected returns to stocks of good companies will be no different from risk-adjusted expected returns to stocks of bad companies.

However, if arbitrage is incomplete, risk adjusted expected returns to stocks of bad companies will exceed risk-adjusted expected returns to stocks of good companies. As we consider arbitrage and the likelihood that it would nullify the effects of the preferences of normal investors on stock price, note that no perfect (risk-free) arbitrage is possible here.

To see the implications of imperfect arbitrage, imagine rational investors who receive reliable, but not perfect, information about the expected return of a particular stock. Imagine also that the nature of the information is such that the expected return of the stock as assessed by rational investors is higher than the expected return as reflected in the current price of the stock. It is optimal for rational investors to increase their holdings of the particular stock, but as the amount devoted to the stock increases, their portfolios become less diversified as they take on more idiosyncratic risk.

Fama (1991) noted long ago that market efficiency per se is not testable. Market efficiency must be tested jointly with an asset pricing model, such as the CAPM or the three-factor model. For example, the excess returns relative to the CAPM of small-cap stocks and stocks with high book-to-market ratios might indicate that the market is not efficient or that the CAPM is a bad model of expected returns.

The definition of “market efficiency” says that a market for a stock is efficient if the price of a stock is always equal to its fundamental value. A stock’s fundamental value is the present value of cash flows the stock can reasonably be expected to generate, such as dividends. Over the years, the definition of “market efficiency” became confused with the notion that a market is efficient when you cannot beat it by earning excess returns (or positive “alpha”).

To earn excess returns, you must identify deviations of price from fundamental value and then buy undervalued securities and sell overvalued ones. Logically, a market that is efficient in terms of the price-equals-fundamental value definition is also a market that cannot be beaten, but a market that cannot be beaten is not necessarily efficient. For example, think of a market in which price deviates greatly from fundamental value, such as during a bubble. Still, you cannot beat the market unless you have a way to take advantage of differences between price and value, and that’s not always possible.

Plenty of investors believed that the stock market was experiencing a bubble in 1998, yet plenty of them lost much money by shorting stocks in 1999. We have much evidence that stock prices regularly deviate from fundamental value, so we know that markets for stocks are not always efficient. Richard Roll (1988) found that only 20 percent of changes in stock prices can be attributed to changes in fundamental value, and Ray Fair (2002) found that many changes in the S&P 500 Index occur with no change in fundamental value. The stock market crash of 1987 stands out as an example of deviation from market efficiency. The U.S. stock market dropped more than 20 percent in one day, October 19, 1987 (popularly referred to as “Black Monday”). No one has been able to identify any change in the fundamental value of U.S. stocks that day that might come close to 20 percent.

The problem of joint testing makes much of the debate on market efficiency futile. Proponents of standard finance regard market efficiency as fact and challenge anomalies that are inconsistent with it. For their part, investment professionals who claim that they can beat the market regard market efficiency as false and delight in anomalies that are inconsistent with it. Standard finance proponents were happy with the CAPM as its asset pricing model as long as it served to show that markets are efficient, but they abandoned the CAPM in favor of the three-factor model when the CAPM produced anomalies inconsistent with market efficiency.

The problem of jointly testing market efficiency and asset pricing models dooms us to attempt to determine two variables with only one equation. Instead, we can assume market efficiency and explore the characteristics that make an asset pricing model, or we can assume an asset pricing model and test market efficiency. I am inclined toward the former. When we see a Toyota automobile in a showroom with one price tag side by side with a Lexus with a higher price tag, we are inclined to look to the automobile asset pricing model for reasons for the price difference rather than conclude that the automobile market is inefficient. Does the Lexus have leather seats while the Toyota’s seats are upholstered in cloth? Does the Lexus nameplate convey

higher status than the Toyota nameplate? The same is true when we see Stock A with an expected return of 8 percent and Stock B with an expected return of 6 percent.

### 3. Research Methodology

This study was a library survey, intended to analyze the available literature on the implications of dynamics of behavioral finance on professional investment practitioner’s strategies. The appropriateness of this method to the study was the ability to review a wide variety of secondary literature that is relevant to the research area

Population of the study comprised of three empirical cases: To establish the implications of dynamics of behavioral finance on professional investment practitioners, the effect of dynamics of behavioral finance on professional investment practitioners strategies and the strategic responses to Global challenges on professional investment practitioners

Purposive sampling technique was used. This method enabled the researchers to select cases that had the desired information or the required characteristics that were useful in achieving the objective of the study.

All these cases were drawn from different sectors in accordance with the research topic. The study made use of only secondary data which was extracted from various published sources as well as the internet. These included books, journals or periodicals among others. Content analysis method was used in view of the qualitative nature of much of the data collected. The method was quite appropriate in the analysis of the contents of documentary materials such as books, journals and internet resources.

### 4. Discussions and Analysis

First, compare investors who rely on fundamental analysis as a strategy with those who rely on technical analysis. Investors using fundamental analysis examine all underlying conditions relevant for future stock price developments. Besides financial statements, these include economic, demographic, and geopolitical factors. In contrast, investors relying on technical analysis only study the stock price movements themselves, believing that historical data provides indicators for future stock price developments.

To us, this suggests that fundamental analysis typically involves more information than technical analysis (cf. Shleifer and Summers, 1990). Investors relying on fundamental analysis are therefore more likely to become more familiar with the firms they follow than investors relying on technical analysis. After all, fundamental analysis serves to focus primary attention on details pertaining to the firms themselves, whereas technical analysis focuses attention on price patterns generated by firms’ stocks.

This focus on firm fundamentals instead of the kind of pattern recognition tasks inherent in technical analysis leads us to conclude that familiarity bias will tend to be stronger by investors relying on fundamental analysis than investors relying on technical analysis. In the language of Kahneman

and Lovallo (1993), investors who rely on fundamental analysis are more inclined to adapt an “inside view” (Kahneman and Lovallo, 1993) and become overconfident than those who rely on technical analysis, as confidence is an increasing function of the amount of information (Locander and Hermann, 1979). We hypothesize that as a result their forecasts become bolder and they more easily overcome status quo bias, leading to less timid choices. Thus, based on condition (2) we expect investors who rely on fundamental analysis to trade more frequently than those who rely on technical analysis, *ceteris paribus*.

Second, compare investors who rely on fundamental analysis with those relying on their intuition. In the behavioral framework, investors do not place high intrinsic value on diversification. In the spirit of prospect theory’s isolation effect (mental accounting, narrow framing) (Kahneman and Tversky, 1979), investors act as if they implement condition (2) on a security-by-security basis, rather than as part of an integrated optimization. As a result, status quo bias will typically lead to under diversification. *Ceteris paribus*, (2) implies that investors holding more securities will tend to be those with stronger convictions in their stock picking skills and in possession of better and more information which leads them to make bolder forecasts (Kahneman and Lovallo, 1993). Only in these cases, will investors be able to overcome status quo bias and be willing to invest in multiple stocks and thus make less timid choices.

As discussed previously, it is likely that the latter features correlate with reliance on fundamental analysis. As such, investors who rely on fundamental analysis will tend to hold a larger number of different stocks in their portfolios than other investors.<sup>11</sup> Conversely, investors who only rely on intuition, and therefore less information, will tend to have less conviction regarding their stock picking skills for most securities and their status quo bias leads them to make timid choices. As a result, these investors may be biased towards a small(er) number of stocks with which they are familiar (Huberman, 2001). Goetzmann and Kumar (2008) point out that as investors increase the number of stocks in their portfolios, they tend to choose stocks which co-move, thereby depriving themselves of the benefits of diversification. Moreover, to avoid feelings of regret (Kahneman et al., 1991) investors relying on intuition will exhibit a strong status quo bias and hold fewer securities in their portfolios.

At Principal Global Equities, they believe that investing in companies with improving business fundamentals, rising investor expectations and attractive relative valuations will result in attractive returns for our clients. But, to deliver attractive returns over time, we believe investors must execute a well defined investment process using systematic methods to ensure consistency.

Global Research Platform systematically evaluates a global universe of stocks using proven models to identify stocks that possess the characteristics we look for in an investment. Leveraging this breadth of research, our fundamental research teams apply years of investment experience to dig deeper into companies’ fundamentals. Their experienced portfolio managers combine proprietary research and

disciplined risk management techniques to construct portfolios that are true to style and driven by stock selection.

## 5. Conclusion

Recent work (Barber et al., 2009) shows individual investors’ tendency to underperform relative to the market. To date, variables which are relatively easy-to-observe such as age, gender, and transaction channel have been used to explain this underperformance and are used as proxies for typically unobservable psychological biases such as overconfidence, loss aversion, and familiarity. To the best of our knowledge, the existing literature has not directly measured these biases using consumer behavior methods such as investor surveys (Graham et al., 2009). Neither has the existing literature positioned its findings of underperformance in a behavioral portfolio framework by employing underlying variables which are less easy-to-observe such as investment objective and strategy.

In this paper we use a unique dataset involving 5,500 individual investors which contains both “hard” accounting and “soft” survey data. We use these data to identify segments of investors based on their dominant investment objectives and the investment strategies they use.

These investor segments are subsequently profiled using a combination of observable and unobservable characteristics.

Finally, the cross-sectional return performance of different segments is analyzed and our behavioral hypotheses tested. Our explanation for differences in return performance between different segments of investors is novel in that instead of using proxies, we use a survey to measure directly investors’ underlying behavioral tendencies and psychological biases. We obtain data on a variety of variables which typically remain unobservable and combine this with a selection of observable variables. As such, we profile investor segments and test the hypotheses of our behavioral portfolio framework.

In doing so, we contribute to the emerging, but limited body of literature investigating latent heterogeneity in finance (Heckman, 2001). Our results might be useful for policy makers, as they show that “the usual suspects” of individuals who trade excessively might differ from the actual culprits. We find that investors using fundamental analysis actually trade more than investors relying on technical analysis, which contrasts with the common belief but fits a behavioral portfolio framework. To the extent that fundamental investors “think” they know the underlying fundamentals that drive stock prices but actually do not, there is a clear target group for educational incentives that has not received the attention it deserves until now. These investors may be provided with questionnaires and self-administered investment quizzes to evaluate their true knowledge about market fundamentals and tailor-made education offered by government agencies or financial authorities.

## 6. Suggestion for Further Studies

Based on these findings mostly from developed countries the researchers recommended a further study on the

implications and strategies of Behavioral finance on professional investment practitioners particularly on developing Countries such as Africa which promises a lot as the next frontier of investment destination.

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