UNIVERSITY OF AGDER

Performance evaluation of behavioral finance mutual funds

A comparison between behavioral finance mutual funds and conventional mutual funds in the Norwegian fund market.

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This Master's Thesis is carried out as a part of the education at the University of Agder and is therefore approved as a part of this education. However, this does not imply that the University answers for the methods that are used or the conclusions that are drawn.

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This master thesis represents the end of my MSc in Business and Administration at the University of Agder. The thesis is a mandatory part of the MSc program and corresponds to 30 ECTS. The objective of a thesis is to apply scientific methods on a practical problem, and should be related to the specialization within the study program.

During the course "Portfolio Management" taught by Steen Koekebakker in the spring 2010, I gained an interest in the mechanics behind irrational markets, and the theory of behavioral finance. This paper has given me the opportunity to learn more about the theoretical background for behavioral finance and irrational markets, as well as applying the theory on real-life testing. I am sure I will benefit from this knowledge in the future and during my working career.

I will use this opportunity to thank Steen Koekebakker for his guidance and tips during the process of writing this thesis. I will also thank all my fellow students for a study-environment based on humor and learning.

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ABSTRACT

Behavioral finance has been gathering more and more attention in the last decade, and both academia and practitioners have slowly starting to accept that psychology influence financial markets. Even though markets are irrational, old theories like CAPM, fundamental analysis and modern portfolio theory is still widely used. Given the amount of research regarding behavioral finance, is it impossible to give a complete summary of the entire field, hence, this study presents a brief review of the most relevant theories in order to give the reader an introduction to behavioral finance.

With the increased attention to behavioral finance, mutual funds seems to incorporate different filters to capture irrational behavioral, and to capitalize on irrational investors. The objective of this study is to evaluate the performance of "behavioral" mutual funds, and to compare their performance to index funds and non-behavioral funds. However, none of the funds in the Norwegian market explicitly admits make investments based on behavioral finance. The selection of funds is therefore based on a detailed and comprehensive review of 67 prospectuses of Norwegian funds, published on the Morningstar and the fund manager's website, is done in order to familiarize behavioral mutual funds in the Norwegian market.

Empirical analysis is further applied, where a test for abnormal performance for six mutual funds identified as behavioral in the Norwegian market is conducted. Further analysis is also performed in order to recognize the strategy approach of the tested behavioral funds.

The empirical results indicate that behavioral funds are able to outperform index funds and non-behavioral funds. The results further indicated that behavioral funds are tilted towards value investing, but fail to earn risk-adjusted abnormal returns. Given the difficulties of identifying behavioral funds in the Norwegian market, it is problematic to draw any strong conclusions from this study, but the results indicate that recognizing behavioral inefficiency may improve the performance of mutual funds.

Keywords: behavioral finance, behavioral mutual funds, market inefficiency, fund performance analysis

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1.0 INTRODUCTION

Over the last decade behavioral finance has gathered more and more attention. Both academia and practitioners are starting to accept that investors do not always make rational choices when making investments. Throughout time behavioral finance has been defined in a numerous ways. Barber and Odean (1998) defined behavioral finance as the human departure from rationality and to incorporate this behavior into standard models of financial markets. Sewell (2007) defines behavioral finance as the influence of psychology in the financial market and how this might explain why the market is inefficient.

If irrational investors are present in the market and the market is inefficient, one could expect mutual funds to outperform the market. However, most studies of mutual fund performance conclude that active managed mutual funds are not able to generate abnormal returns (Jensen, 1968; Wermers, 2000). To further expand the research on fund performance and the practical application of behavioral finance, this study examines if mutual funds can benefit from behavioral finance.

Mutual funds that that explicit applies a behavioral strategy approach may be categorized as behavioral. However, defining what makes a mutual fund "behavioral" is difficult, and involves some subjectivity. Wright et al. (2006) define behavioral mutual funds as funds that "claims to base their investment strategies on principles of behavioral finance in order to capitalize on market inefficiencies and earn above average returns" (Wright et al., 2006).

There are two main international studies of behavioral mutual fund performance, and these studies have found similar results: Reinhart and Brennan (2007) found that behavioral funds were able to outperform index funds and their respective Morningstar and Lipper indices. Wright et al. build further on the work of Reinhart and Brennan by adding more funds to the data sample and by using a multifactor risk model, in order to evaluate the funds performance. Their results indicate that behavioral mutual funds are able to attract investment dollars, outperform index funds, but have not been able to deliver risk-adjusted abnormal returns.

Due to the lack of earlier studies concerning behavioral finance in the Norwegian market, the purpose of this study is to identify and analyze the performance of behavioral funds in the Norwegian market. The funds are identified after a comprehensive review of 67 Norwegian mutual funds using their prospectuses published on Morningstar, and examining the investment philosophy of the funds management company. However, none of the funds in the Norwegian market explicitly admits make investments based on behavioral finance, which caused the categorization to be difficult. The analysis is conducted to examine whether behavioral mutual funds (1) earn abnormal returns after controlling for risk and (2) have different factor loading in the Carhart four-factor model compared to non-behavioral funds. The Norwegian behavioral mutual funds included in this study are Skagen Vekst, Pareto Aksje Norge, Delphi Norge, Pluss Aksje, Holberg Norge and Odin Norge.

The study starts with a general test for abnormal performance. After the test for abnormal performance, each funds is ranked using Sharpe Ratio and Information Ratio in order to analyze their ability to outperform the market and index funds. To further compare the funds associated with behavioral finance against traditional active managed funds, two equally weighted portfolios are created and tested using the same measurements.

I expect my empirical result to support the finding of Reinhart and Brennan (2007) and Wright et al (2006), that behavioral mutual funds in the Norwegian market outperform index funds and non-behavioral funds, but being unable to generate risk-adjusted abnormal returns.

The empirical results confirm my expectations, that behavioral funds are unable to generate risk-adjusted abnormal returns. My finding also indicates that the funds are able to outperform index funds. Additionally, the result indicates that behavioral fund seems to be more tilted towards value investing than non-behavioral funds.

Similar to Wright et al., I would emphasize the difficulties of identifying behavioral funds. However, the funds included in this study are the funds with the strongest characteristics towards a behavioral strategy.

1.1 HYPOTHESIS

The main objective of this study is to determine: (1) If Norwegian behavioral mutual funds can earn positive abnormal returns and (2) try to gain insight in the strategy the funds follows by analyzing the factor loadings in the Carhart four-factor model.

The following hypothesis is formed in order to evaluate the objective of the study:

H1: Behavioral mutual funds earn zero abnormal returns after controlling for risk.

H2: Behavioral mutual funds load differently than conventional mutual fund on the Fama and French (1992) and Carhart (1997) factor portfolios.

The reminder of the paper proceeds as follows. Section two provides the theoretical background for the rational approach of asset pricing and can be seen as a review of the most relevant literature. Section three introduces behavioral finance as an alternative theory to the rational approach. Section four contains a short summary of studies evaluating mutual fund investing and performance. Section five describes the data used in the empirical testing, while section six lays out the results of the testing. Section seven contains the concluding remarks.

2.0 THE RATIONAL APPROACH TO ASSET PRICING

In Section 2.1 the efficient market hypothesis is introduces, and the basic literature is reviewed. Section 2.2 and 2.3 introduce the capital asset price model and the arbitrage pricing theory. Section 2.4 and section 2.5 explains the notion behind the multifactor models of Fama and French (1992) and Carhart (1997). In section 2.6 the implication of efficient markets for portfolio management is discussed.

2.1 EFFICIENT MARKET HYPOTHESIS

The Efficient Market Hypothesis (EMH) is today the most used and well-respected theory for estimating future stock prices. Ever since Eugene Fama published his "Random Walks in Stock Market Prices" in 1965, the theory has been one of the building blocks in traditional finance, and is thought in all introductory finance class.

Fama (1965) defines an efficient market as "*a market where there are large numbers of rational profit maximizes actively competing, with each other trying to predict future market values of individual securities, and where important current information is almost freely available to all participants*". This indicates that competition is free, and every participant is the market is trying to profit as much as possible. Efficient markets also imply that prediction of future stock prices is impossible, as they follow a random walk.

According to Samuelson (1965) the information available in the market, makes up a set of three efficient-levels:

- Week form efficiency: Stock prices reflect historical prices and other financial data. Future stock price move according to a random walk, and any mispricing in the market will be eliminated the second they are observed by competing investors. Under this efficiency, technical analysis will not work, since all historical information is useless.
- Semi-strong efficiency: In this form for efficiency, all public information is reflected in the stock price. This implies that both technical and fundamental analysis will be useless. Under this efficient the only way to create excess returns is either by luck or inside information.
- Strong efficiency: Stock prices reflect all information, both public information and inside information. Under this efficiency it is not possible to create excess return.

In an efficient market both information- and transactions costs are not considered relevant. While Jensen (1979) argue that profitable trade would be made until the cost of transaction and information is equal to the margin cost, Fama (1991) finds it more relevant to test for efficiency without any considering any costs.

The paradox of the efficient market hypothesis is that if every investor believes the market is efficient, the market would not be efficient. In this case no one would be analyzing securities in the search for undervalued securities. The market need investors in search for information and undervalues securities in order to stay efficient. This also implies that the information in stock analysis forms the basis for the "right" market price (Grossman & Stiglitz, 1980; Reizer, 2010).

The level of efficiency in the market is still a topic under discussion. Studies show a semi-strong market both in the US and in Norway, and this is supportive to the expectations considering that new technology enables investors to gather and process all information in the market rather quickly. Studies of fund performance can also be used to test the level of efficient. Both Gjerde and Sættem (1991) and Sørensen (2009) found active managed funds not being able to earn abnormal returns, indicating at least a semi-strong efficiency in the Norwegian market.

2.2 Capital Asset Pricing Model

The capital asset pricing model, (CAPM), was developed by William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966), and build on the work about modern portfolio theory published by Harry Markowitz (1952). The model gives a prediction of the return and systematic risk of a portfolio, and could be used to provide a benchmark for evaluation investments and to make an educated guess about expected returns. CAPM suggests that the optimal portfolio for a mean-variance optimizing investor, is a combination of the risk-free asset and the market portfolio (Bodie et al., 2008).

The CAPM is built up on six strict assumptions, and under these assumptions most of the complexity regarding the market is ignored:

1. The market consists of many investors, all with a small wealth compared to the market. All investors are considered to be price takers.
2. All investors plan for only one time horizon, indicating they are shortsighted.

3. The investor can choose between all publicly traded financial assets and risk-free borrowing and lending.
4. All investor are rational, mean-variance optimizers.
5. The investors pay no taxes on returns and no transaction costs on trades in securities.
6. Investors have homogeneous expectations about securities and the market.

The model is defined as:

$$E(r_p) = r_f + \beta_p * [\mathrm{E}(r_m) - r_f] \tag{1}$$

where

$E(r_p)$	=	Expected return on the portfolio
r_f	=	Risk-free interest rate
$\mathrm{E}(r_m)$	=	Expected return on market
$\mathrm{E}(r_m) - r_f$	=	Expected market risk premium
β_p	=	Portfolio beta (systematic risk)

To capture movement in the portfolio relative to the market, beta is introduced. Beta is the sensitivity of the excess return of the portfolio, relative to the expected excess return on the market, and defined as:

$$\beta_p = \frac{Cov(r_p, r_m)}{\sigma_m^2} \tag{2}$$

where

$Cov(r_p, r_m)$	=	Covariance between return on the portfolio, and return on the market.
σ_m^2	=	Variance of the market.

The market portfolio has a β of 1, and if portfolio has a β higher (lower) than 1 the portfolio will fluctuate more (less) than the market portfolio. The CAPM considers only systematic risk and not unsystematic risk related to companies, due to the assumption about all investor being well diversified.

The risk related to the return on securities is measured trough standard deviation, which is calculated as average difference from the average return. A security with volatile returns holds a high standard deviation relative to a less volatile security. When analyzing fund performance, standard deviation can be used in order to test the performance of the fund manager. A fund with high returns can hold a high standard deviation and thereby not yield any better risk-adjusted returns, since the high returns are directly related to high risk.

The standard deviation of a mutual fund is referred to as the total risk, and can be divided in systematic and nonsystematic risk (Bodie, et al., 2008).

Total risk is defined as:

$$\sigma_p = \beta_p * \sigma_m + \sigma_e \tag{3}$$

where

σ_p	=	Total Risk, Variance of the portfolio
$\beta_p \sigma_m$	=	Systematic risk
σ_e	=	Nonsystematic risk

The systematic risk is related to the aggregate market and thereby referred to as market-risk or undiversified risk. Since the systematic risk represents the correlation between return on the market index and return on the portfolio, the systematic risk cannot be mitigated through diversification. A major part of the systematic risk is related to news and events on a macro level. Changes in oil prices, political issues, and interest-rates are factors contributing to fluctuation in the systematic risk (Wittrup, 2008). One recent example of increase in systematic risk is the financial crisis in 2008, which lead to stock markets plummeting and interest rates being driven up. This caused the value of both securities and funds to fall sharply.

The unsystematic risk is the risk a fund is accepting when moving away from the market portfolio. Unsystematic risk often referred to as firm-specific risk or diversifiable risk, as holding a well-diversified portfolio removes all unsystematic risk. In active fund management where stock picking is used, the fund is accepting risk on a micro level. This may be financial distress, strike, production problems or any other risk uncorrelated with the aggregate market risk. The market portfolio holds no unsystematic risk, since all securities are included in the market portfolio.

To lower the total risk in the portfolio the investor or fund manager can use diversification. Markowitz (1952) showed that, as long as stocks fluctuate differently, including more stocks would lower the total risk of the portfolio. Statman (1987) found that a well-diversified portfolio consist of a least 30 stocks.

By reformulating the CAPM into an index model, it can be used to test historical realizes return relative to expected returns.

The single index model is the defined as:

$$r_{pt} - r_{ft} = \alpha_{pt} + \beta_p\left(r_{mt} - r_{ft}\right) + \varepsilon_{pt} \tag{4}$$

where

r_{pt}	=	Realized return on portfolio p, in time period t.
r_{ft}	=	Risk-free interest rate at time period t
α_{pt}	=	Realized abnormal return in time period t
$\left(r_{mt} - r_{ft}\right)$	=	Realized market premium in time period t.
ε_{pt}	=	Residual returns

The single-index model can be estimated using a regression model. Historical observations are used in order explain the linear relation between market return and return on the portfolio. By using the single-index this way, the model is assuming that previous performance is equal to the expected return.

This regression analysis is based on the principle of Ordinary Least Squares (OLS). This method minimizes the sum of the residuals by minimizing the distance between the estimated regression line and the historical observations on the dependent variable (Greene, 2008). β_p is the regression-coefficient and explains how much a marginal change in the independent variable, the market portfolio, would change the depended variable holding all other variable constant. The β_p in CAPM measures how close the portfolio follows movements in the market. α is the intercept of the regression, and explain the abnormal performance. This will be further discusses in section 2.7.2 as Jensen's alpha.

The error term ε_i holds a variance of zero, and is a measurement of the unsystematic risk related to the model. The error term captures the variation in the dependent variable, which is not explained by the independent variables. Variations such as wrong measurement, wrong independent variables or outliers in the observations, could influence the error term.

To determine if the model produces statistical significant regression coefficients, a standard t-test may be applied. T-values are computed by dividing the estimated regression coefficient over standard error. As a general rule, the t-value for a 95% confidence interval should not exceed a critical absolute value of 1.96. If the t-values exceed the critical value, the null hypothesis is rejected since the values estimated by the model does not hold as statistical significant. When testing for abnormal performance, the following hypotheses are formed:

$$H_0: \alpha = 0$$
$$H_1: \alpha \neq 0$$

If the t-value for an alpha test exceeds 1.96 the variable is found to be different from zero at a 5 % significant level.

2.3 ARBITRAGE PRICING THEORY

An alternative model to describe the returns of securities is the arbitrage pricing theory (ATP) developed by Stephen Ross (1976). The theory relies on three propositions: First, a factor model can be used to describe returns on securities. Second, the market consists of enough securities to diversify away all nonsystematic risk. Third, well functioning security market does not allow arbitrage opportunities to persist.

By dividing the risk in the security in macro events and company specific events, a multifactor model can be derived. The argument behind the model is that different macro events in the business cycle might affect expected stock return. By introducing factor portfolios for each of the different systematic risk factors, the model can be used to analyze how each of the risk factors affects the stock returns. Factor portfolios are well-diversified portfolios constructed to have a beta of 1 to the specific systematic risk factor and beta of 0 to all other risk factors. Common risk factors in the model are oil price, inflation rates fluctuation, GDP and industrial production. Each risk factor has an excepted value of zero, which indicates that the level is irrelevant, and only changes in the level are considered to be a risk factor.

The multifactor APT can be defined as:

$$r_p = E(r_p) + \beta_{p1}F_1 + \beta_{p2}F_2 + \cdots + \beta_{pn}F_n + \varepsilon_p \tag{5}$$

where

r_p	=	Return on the portfolio
$E(r_p)$	=	Expected return on the portfolio
β_{pn}	=	Factor loadings
F_n	=	Factor portfolios

The APT has less strict assumptions than CAPM and can be regarded as more robust model. In contrast to the CAPM, the APT makes no explicit assumptions about investors' utility function and does not consider an unobservable market portfolio. As mention earlier, the model also uses factor portfolios to track the sensitivity of returns relative to common risk factors. The model further implies that any arbitrage opportunity in the market will be exploited, and a violation of the APT would cause extreme pressure to restore equilibrium.

As the APT assumes both frictionless and competitive markets, the practical application of the theory has been widely discussed. Frictionless markets means no transaction cost, while a competitive markets is referring to a market where buyer and sellers can trade unlimited quantities of the security without changing the price of the security. Relaxing these assumptions makes the theory more practical useful, but also introduce the notion of liquidity risk. Studies have found the liquidity risk makes the "correct" price under APT into an arbitrage-free interval rather than one specific arbitrage-free price.

One practical application of APT is style investing. By creating factor portfolios on certain areas in the market, it is possible to sell different investments styles to the investor. One company who sell such styles is Dimensional Fund Advisors. They offer the opportunity to investing in factor portfolios like SMB or HML (Bodie, et al., 2008; Cetin et al., 2004).

2.4 FAMA-FRENCH THREE FACTOR MODEL

In 1992 Eugene Fama and Kenneth French extended the CAPM. By analyzing stocks on NYSE, AMEX and NASDAQ they observed that stock with small capitalization earned higher average return than stock with large capitalization, and similar, stocks with high book-to-market ratio would earn higher average returns than stocks with low book-to-market ratio. Their results indicates that stock returns are multidimensional, and to better explain the variations in stock prices caused by these cross-sectional returns in the market, they added two risk factors to CAPM. To capture the risk-reward related to firm size, they added the SMB factor, and for the book-to-market ratio the HML factor was added.

The Fama-French model is defined as:

$$r_p - r_f = \alpha_p + \beta_p RMFR + s_p SMB + h_p HML + \varepsilon_p \quad (6)$$

SMB is the risk factor related to firm size, and stands for small minus big. Fama and French construct this factor by creating two portfolios, one of the smallest 30% of the stocks and one of the largest 30%. The SMB factor is then calculated by subtracting the average return of the portfolio consisting of large stocks from the average return of the portfolio consisting of small stocks. A positive (negative) SMB-factor indicates that small-capitalized stocks have overperformed (underperformed) relative to large capitalized stocks. The SMB factor is added to address the risk related to less liquidity and the less ability of small stocks to absorb negative financial events (Barberis et al., 1998)

The factor HML is added to capture the risk related to book-to-market ratio. Fama and French created this factor by sorting all stock by their book-to-market ratio. Then they created two portfolios by dividing stocks in two portfolios: value stocks with high book-to-market ratio and growth stock with low book-to-market ratio. The HML factor is then calculated as the average return of value stocks, minus the average return of the growth stock. A positive (negative) HML factor indicated that value stocks have overperformed (underperformed) relative to growth stocks. The HML factor is added as a risk factor to capture the risk related to beliefs about future earnings or financial distress (Barberis, et al., 1998; K. C. Chan & Chen, 1991).

The model explains the relationship between risk-reward and thus ads support to hypothesis about efficient market. Fama and French argue that the return on a security is only a result of exposure to different risk factors, and this indicates that investors are not able to generate abnormal return. Any investor claiming this ability, has only adjusted the relative factor loading, and accepted the risk involved (Fama & French, 1992).

2.5 CARHART'S FOUR-FACTOR MODEL

To explain even more of the variability in the return on a portfolio, a third factor is added to CAPM. Hendricks et al. (1993) introduced the term "hot hands" by studying the short-time persistence in mutual funds performance. Their result indicates that selecting among the top performers based on the results last four quarter could outperform the average mutual funds. Jegadeesh and Titman (1993) further studies the returns of stocks, and discovered the prior one-year momentum anomaly. This anomaly indicated that prior winners continue to outperform prior losers with an average of about 1% per month. Jeagdeesh and Titman (1993) attributes this different to the fact that investors react slow to new information. The result of Carhart (1997) indicates that the momentum anomaly in stock returns leads to the phenomenon of hot hands in mutual funds performance. To better capture this anomaly, Carhart added the prior-one-year-momentum factor to the Fama and French (1992) three-factor model in order to examine portfolio performance. The PR1YR is constructed *"as the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month"* (Carhart, 1997). The model can also be interpreted as a performance attribution model, where the coefficients on factor portfolios attributes for four strategies: High versus low beta stocks, large versus small market capitalization stocks, value versus growth stocks and one-year momentum versus contrarian stocks.

The Carhart four-factor model is defined as:

$$r_p - r_f = \alpha_p + \beta_p RMRF + s_p SMB + h_p HML + h_p PR1YR + \varepsilon_p \qquad (7)$$

SMB, HML and PR1YR are returns on the factor portfolios related to size, book-to-market ratio and momentum.

Carhart finds certain persistence in mutual fund performance, but most of the funds underperform relative to the index. This is in line with earlier studies indicating that active portfolio management is not able to deliver abnormal return above the market (Burton, 1995; Fama & French, 1992; Wermers, 2000). The results of Carhart also indicate that following a momentum strategy earn significantly lower abnormal returns after transaction expenses. He suggests that transactions cost consume the gains from the momentum strategy. Carhart further finds that four-factor model being able to eliminate almost all of the pricing error, meaning that it well "*describes the cross-sectional variation in average stock returns"*. He further lists three rules for investors; first, avoid funds with persistent bad performance. Second, only one-year persistence can be observed. Third, costs have direct negative impact on the performance of the funds (Carhart, 1997).

2.6 IMPLICATION FOR PORTFOLIO MANAGEMENT

Under the rational approach to asset pricing, combining the market portfolio with a risk-free asset achieves the best risk-adjusted returns. This means that both risk loving and risk-averse investor should consider investing in passive managed funds, since the fund will follow the movement of the market portfolio, and thus, in combination with a risk-free alternative, generate the best risk-adjusted return (Bodie, et al., 2008).

A passive managed fund tries to replicate an index, and is often called an index fund. To implement the strategy, the fund manager invests in all the companies in an index, and rebalances the portfolio only when changes are done to the index. Each company is given the same weight in the portfolio, as in the index, and the return on the fund will follow the return on the index and not try to outperform it. The fund manager only replicates the index, indicating that stock picking and analysis is eliminated, reducing the holding cost on index funds. With only limited changes in the index, an index fund will be relative cheaper to hold compared to an active managed fund. The index fund should be appealing to investors who are skeptical about fund managers' ability to outperform the market, and to those who would like to minimize the transaction costs.

In Norway only a few index fund are available to investors, but the number of available index funds are increasing steadily. In addition to the traditional index funds sold direct from fund companies to investors, it is also possible to buy index funds directly on the Oslo Stock Exchange. These funds are called Exchange-traded funds (ETFs) and traded similar to stocks. Since ETFs are traded throughout the day, prices are available at any time, and the investor has no costs related to buying and selling, other than the normal fee to the broker as similar to stocks.

2.6.1 PORTFOLIO PERFORMANCE MEASUREMENT

Even though the CAPM and the efficient market hypothesis suggest that the best risk-reward is achieved by combing the risk-free asset and the market portfolio, there are still many fund managers trying to outperform the market. This is done through active management of the funds. To test the ability of the fund manager to achieve a better risk-reward performance, three different performance measurements are introduced. In this section Jensen's alpha, Sharpe Ratio and Information are introduced to give a better understanding of portfolio performance.

2.6.2 JENSEN ALPHA

Jensen (1967) developed a risk-adjusted measurement to test the ability of fund managers to earn returns higher than expected by the CAPM, given the β of the portfolio and the return on the market.

Jensen's alpha is defined as:

$$\alpha_p = E(r_p) - \left[r_f + \beta_p\left(E(r_m) - r_f\right)\right] \tag{8}$$

In this model the alpha, α_p, represents the abnormal return above the return expected from CAPM. Under CAPM, the investor is expected to receive $\alpha_p = 0$ and the only factor contributing to increased expected return above the risk-free interest rate, is the systematic risk β_p. Jensen's alpha can also be computed using a multiple factor model such as Fama and French (1992) or the Carhart (1997) model.

Since Jensen's alpha is an absolute measure of performance, a positive alpha would indicate that the portfolio has outperformed the market on a risk-adjusted basis. A negative alpha indicated that the portfolio did worse than the market, after adjusting for risk.

Under active fund management, the manager tries to identify securities that yield returns above the security market line, earn excess returns. In this context Jensen's alpha can be used as a measure of the success of the portfolio manager

The model assumes a constant beta-value and a constant risk-free rate. However, a constant beta is problematic due to shifts in the portfolio. Further, the use of a risk-free rate is problematic since there is no "official" risk-free rate. Since Jensen's alpha measure performance relative to a market index, selection of benchmark index can also influence the result.

2.6.3 SHARPE'S RATIO

Introduced by William Sharpe in 1966, the Sharpe Ratio is used as a "reward-to-variability ratio" to measure performance of mutual funds.

The ratio is created to measure excess return per each unit of total risk in the portfolio. This way the Sharp's Ratio can be used to check if a fund return is due to smart decisions or a result of excess risk. The Sharpe Ratio produces arbitrary values and can only be uses as a way to rank the performance of different portfolios.

Sharpe's ratio is defined as:

$$S_p = \frac{R_p - R_f}{\sigma_p} \tag{9}$$

where

S_p	=	Sharpe Ratio
R_p	=	Portfolio return
R_f	=	Risk-free rate
σ_p	=	Standard deviation of the portfolio

2.6.4 INFORMATION RATIO

Information Ratio (IR) is used as a measure of abnormal returns relative to a benchmark portfolio, per unit of nonsystematic risk, the risk that in principle can de diversified away by holding the market portfolio.

Information Ratio is defined as

$$IR_p = \frac{R_p - R_b}{\sigma(R_p - R_b)} = \frac{\alpha}{\omega} \tag{10}$$

where

IR_p	=	Information Ration on the portfolio
$R_p - R_b$	=	Active returns, difference between return on the portfolio and benchmark returns
$\sigma(R_p - R_b)$	=	Tracking error, standard deviation of the active returns.

IR is used as a measure to test the skill of fund managers. By measuring the active returns divided by the amount of risk taken by the fund manager, relative to the selected benchmark. The higher the IR, the better the fund manager has performed. A statistical significant IR equal 0.5 can be regarded as good, while 0.75 is very good and IR equal to 1 is exceptional good (Goodwin, 1998)

3.0 The Behavioral approach to asset pricing

Section 3.1 introduces behavioral finance as a theoretical alternative to the efficient market hypothesis and to give an explanation for the existence of such theory. To give an overview of the building blocks of behavioral finance, limits to arbitrage and psychology is introduced in section 3.2 and section 3.3. To further explain some of the implication in the market cross-sectional returns is explained in section 3.4, while the implication for portfolio management is explained in section 3.5

3.1 Behavioral finance

"Modern financial economics assumes that we behave with extreme rationality; but, we do not. Furthermore, our deviations from rationality are often systematic. Behavioral finance relaxes the traditional assumptions of financial economics by incorporating these observable, systematic, and very human departures from rationality into standard models of financial markets" (Barber & Odean, 1998, p. 25).

Under the rational approach to asset pricing, all agents are expected to always behave rational, and to make decisions under perfect assumptions. However, both psychological and empirical researches show that agents are *not* fully rational (Barber & Odean, 1998; Dittrich et al., 2001; Kahneman & Tversky, 1979). Behavioral finance tries to give a understanding of what happens when agents act irrationally, and thereby, develop new models to better explain movements in the financial market (Barberis & Thaler, 2002). Furthermore, behavioral finance uses models that accept irrational agents, and tries to cope with it, rather than neglecting it. In contrast to the efficient market hypothesis, behavioral finance has not been able to produce a unified mathematical framework that explains the variation in stock prices. However, the field is still developing and more and more scholars are accepting the presence of irrational investors in the market.

Behavioral finance has mainly two building blocks; limit to arbitrage and cognitive psychology (Ritter, 2003; Shleifer & Summers, 1990).

1) Limit to arbitrage refers to the amount of irrational traders in the market, making arbitrage possibilities to conserve.
2) Cognitive psychology refers to how people behave, and there is a huge amount of psychology literature documenting that people do not always make rational choices.

3.2 LIMITS TO ARBITRAGE

Arbitrage can be defined as “*The exploitation of security mispricing in such a way that risk-free profits can be earned (...)*” (Bodie, et al., 2008).

Under the rational approach to asset pricing, security prices are assumed to always be equal to the “fundamental value” and prices are seen as “right”. This indicates that rational agents would quickly adapt new information in the market, and act according to Bayes’ law. Rational agents would then exploit any arbitrage possibility in the market, and thus constantly adjust the price according to the “fundamental value”. In contrast, behavioral finance suggests that even though arbitrage possibilities exist, not all such opportunities would be utilized, because of different risk factors

Barberis and Thaler argue in their 2002 article “A survey of behavior finance” that in the efficient market “prices are right” means “no free lunch”, and similar “no free lunch” means “prices are right”. In the inefficient “behavior finance market”, “prices are right” also means “no free lunch”, but “no free lunch” does not implies “prices are right”. This indicates that even though there is a mispricing in the market, there is necessarily not any excess risk-adjusted average return for the taking. This is one of the key differences between the rational and the behavioral approach to asset pricing.

Shleifer and Summer (1990) refers to two types of risk related to limit to arbitrage; fundamental risk and movement in investor sentiment, referred to as noise-trader risk. Traders who act on non-fundamental info can be defined as noise traders, since they consider noise in the market as information. Shleifer and Summer argues that since arbitrage should be risk-free, irrational investor-behavior limits the arbitrage opportunities.

Shleifer and Visny (1997) further studied this argument They conclude that specialized arbitragers may avoid arbitrage-opportunities due to extreme high volatility, and the possibility of a loss leading to liquidation of the portfolio. They suggests that even being an opportunity to profit, not all arbitrage positions in the market will be traded. Barber and Thaler (2003) also adds implementation cost as a limiting factor, while Montier (2002) adds the risk of financing.

3.2.1 Fundamental Risk

Fundamental risk refers to the risk of an arbitrager being wrong about the positions taken (Montier, 2002). Since arbitrage is going long in one security and short in another, to earn a risk-free profit, fundamental risk also refers to the relative mispricing between securities.

The fundamental risk can be illustrated by going long stock A and short stock B. If stock A releases good news, justifying the higher price of stock A, the arbitrage-position must be closed with a loss. The mispricing was present due to release of good news and not as a risk-free mispricing in the market.

While the arbitrage-strategy may reduce some industry wide risk in the position, not all the fundamental risk can be eliminated. Barberis and Thaler (2002) exemplify this by going long car manufacturer Ford and short GM, at the time when GM bought Ford. The arbitrager is then exposed to risk related to Ford, but, to a certain degree, protected from negative news regarding the car industry as a whole.

3.2.2 Noise trader risk

According to Black (1986), Kyle (1985) and Long et al. (1990) noise traders are irrational investors who base their investment decisions on their own research. Since these investors do not have any the inside information, they irrationally act on noise in the market. The notion is that noise traders believe that noise in the market can be regarded as information. While fund managers and other professionals often hold the same view on stocks or the aggregate market, noise traders may have a different perception and thereby making prices move away from the expected level. For an arbitrageur the presence of noise traders involves both an opportunity to profit, but also a constant risk. Montier (2002) divides the noise trader risk in three; horizon risk, margin risk and short covering risk.

Horizon Risk

Shleifer and Visny (1997) found that in short time horizons, arbitragers is exposes to horizon risk due to the time element of the investment. Since noise traders do not care about the “fundamental” value, arbitragers can experience larger deviations from the “fundamental” value in short run. The length of time needed for the price to revert back to the “correct” value may reduce the arbitragers’ return dramatically. The horizon risk can be exemplified this way;

if a 5% underpricing is corrected in one month, the annual rate of return is almost 80%, but if the correction takes two years the annual rate of return is below 2.5%.

MARGIN RISK

Arbitragers often use debt to buy into positions, and if the arbitrage-position moves against the arbitrager, it is likely to be faced with a margin call. The arbitrager may then be forced to liquidate the position, causing potential losses. Another problem for the professional arbitragers is that they often hold position for others, and due to margin risk, trades with high volatility may be left untouched (Montier, 2002).

Liu and Longstaff (2000) claims that being exposed to margin risk, the optimal strategy where maximal profit is reached, is less likely to occur. Barberis and Thaler (2002) also stress the facts that if a creditor sees the value of the collateral erode, they will likely call back the loans, forcing liquidation of the position.

SHORT COVERING RISK

As the arbitrageur needs to hold a short position in one security he is exposed to short covering risk. If the securities which are held short is called back by the owner, this may force a premature liquidation of the position (Montier, 2002).

3.2.3 PRINCIPAL-AGENT PROBLEMS

Another problem, which cause arbitrage to persist in the market, is the separation of brain and capital. Highly specialized arbitragers manage most arbitrage-funds in the market, and since they invest other peoples capital, there is "*a separation of brains and capital*" (Shleifer & Vishny, 1997). Following this argument, Montier (2002) points out three different principal-agents problems:

1) Since the market for arbitrage is highly specialized, it is hard for the investors to understand the market, and thereby separate good arbitrager from bad arbitrager. Since investors are risk-averse and only provide a certain amount of capital, the arbitrager is capital-constrained.
2) Since investors base their investment decisions on previous performance, funds with a good historical performance will easily attract new capital, while funds struggling in the

past will have problems gathering new capital. This will again leave some arbitragers capital-constrained, indicating that persistence performance is valuable.

3) The arbitrageurs' knowledge is constrained due to the high specialization in the market. This means that an arbitrageur in the forex market stays in the forex market, and similar with the bond market, keeping the markets segmented.

Montier further argues that these three principle-agent problems are most important under extreme conditions. When the mispricing is large, the arbitrager is aware of the possible profit, but due to capital-constrains, he is unable to take advantage of the opportunity. The best example of the principle agent problems is the hedge fund Long-Term Capital Management, which had to liquidate positions due to margin calls and capital constrains.

3.2.4 IMPLEMENTATION COST

The last risk factor under limits to arbitrage is the implementations costs. Cost is always influencing investments decision and arbitrage-possibilities may be left untouched due to high implementation costs. Borrowing stocks is especially costly and can reduce the profit heavily. The fees for borrowing stocks is normally 10 to 15 basis point, but due to noise traders, it may in some situations be almost impossible to borrow stocks at *any* price, since the demand curve for borrowing stocks is upward sloping. This increases the implementations costs and may let arbitrage possibilities remain in the market (D'Avolio, 2002).

3.2.5 EVIDENCE OF LIMITS TO ARBITRAGE

Under the law of one price and the efficient market hypothesis, two similar stocks with identical cash flows should have the same price. If that is not the case, the law of one price does not hold, and the efficient market hypothesis is violated. The twin-stock phenomena and some famous equity cave-outs seem to violate this basic principle.

TWIN STOCKS

In 1907 Royal Dutch and Shell Transport decides to merge interests with a 60/40 basis, but still remains as separate companies. Royal Dutch traded mainly in USA and in the Netherlands, while Shell mainly traded in UK. With a 60/40 merge, Royal Dutch should always be worth 1.5 times Shell. Froot and Babora (1999) analyzed the case of Shell and Royal Dutch and found a deviation from the theoretical parity of -30% to +20%. They were not able to explain this large deviation from the parity by fundamental factors, meaning something else was influencing the price deviation. However, they did find the relative price being correlated to the relative price of the indexes where the twins stocks were listed. Barberis and Thaler (2002) later found this case revealing limits to arbitrage due to high noise trader risk. In 2001 the stocks finally converged and sold at par.

Another example is Unilever PLC. and Unilever N.V. In 1930 the companies formed an agreement to equalize cash flows, and to act as a single group company. After the deal was completed, the two stocks used 15 years to converge, and finally to trade at par. Froot and Babora (1999) found this long period of mispricing was present due to country-specific sentiments. Their study also revealed that even if the investors were rational, the markets were too fragmented, causing a two-price system due to transaction costs and agency problems.

EQUITY CARVE OUTS

When a company decides to sell out a specific part of company itself, is it often done by an equity carve-out. Between 1998 and 2000 several equity carve-outs showed mispricing in the market, and because of the shorting cost, these mispricings were not exploited (Lamont & Thaler, 2001). One example of mispricing in the market after an equity carve-out is the case of 3Com and Palm. In 2002, 3Com decided to carve out Palm by issuing an IPO, and at the same time give each 3Com owner 1.5 stocks in Palm. The relative price should then give a value of 3Com similar to 1.5 times the value of Palm. However, the market used 5 months to close this gap. This was a massive arbitrage opportunity, but since private investor owned most of the stocks, the implementation cost related to shorting stocks was huge and limited the arbitrage possibilities

3.3 Psychology

Since agents are not always mean-variance optimizers, they make mistakes when investing. Often are rules-of-thumb used as guidance when dealing with huge sets of information (Montier, 2002). In this section, the most relevant findings from studies of common psychological traits are presented. To understand how psychology affects investors rationality, surveys are often conducted to find, and explain, anomalies in the financial market.

3.3.1 Over-confidence

One common mistake done by investors is to "*systematically overestimate the accuracy of one's decisions and the precision of one's knowledge*" (Dittrich, et al., 2001). Overconfidence is often referred to as miscalibration, and can be tested by using a calibration test. Studies of calibration tests, reveals that overconfidence is largest when the answer is hard to predict, or if the result does not give any clear feedback (Koriat et al., 1980). The result of Koriat et al. (1980) confirms that stock picking is a subject where people generally tend be overconfident. Odean (1998) examined 10.000 discount accounts and found, partly because of overconfidence, that the returns were on averrage lowered by high trading activity. Further research also finds that men is more overconfident than women and thereby trade more, reducing theire performane (Barber & Odean, 1998).

3.3.2 Over-optimism

"Perhaps the best documented of all psychological errors is the tendency to be over-optimistic. People tend to exaggerate their own abilities. Like the children of Lake Woebegone, they are all above average. For instance, when asked if they thought they were good drivers, around 80% of people say yes! Ask a room full of students who thinks they will finish in the top 50% of the class, on average around 80% of them will respond in the affirmative — of course at least 30% of them will be disappointed at the end of the course" (Montier, 2002)

Studies show that both private investors and fund managers are over-optimistic about the future earnings, even if the company is expecting losses. The anomaly of over-optimism also includes the planning fallacy; people are over-optimistic about the timeframe of different tasks, like completing a thesis. This may be due to the illusion of control and self-attribution bias (Montier, 2002).

Also a second survey finds that investors seem to be over-optimistic about future earning, even if the company itself is expecting losses. When the company posted their negative earnings, the investor was disappointed and the stock fell significantly more than stocks without optimistic expectations (Ciccone, 2003).

3.3.3. ANCHORING AND ADJUSTMENT

Anchoring is the heuristic that explain that people will base their answer or decision on an initial "anchor", and then adjusts according to believes, to yield their final answer. By using a survey, Kahneman and Thaler (1979) found that spinning a wheel of fortune in front of the participants, adjusted their answer to any arbitrary question. The study revealed the answers being highly correlated with the value on the wheel of fortune. Kahneman et al. (1982) further studied this heuristic. They asked two groups of high school students to estimate the product of an equation within five seconds: One group was asked to estimate 1*2*3*4*5*6*7*8, while the other group was asked 8*7*6*5*4*3*2*1. They found the median estimate answer for the ascending sequence to be 512, while the estimate for the descending sequence was 2.250. The correct answer is 40.320. The way this question was asked, clearly affected the answer, due to anchoring (Kahneman et al., 1982).

Montier (2002) asked fund managers about the end value of Dow Jones Industrial Average (DJIA) if one included the dividends. While most fund manager based their answer on the DJIA level at that time, 9181, and then doubled or tripled this value, the correct value would have been 652.230 (Fisher & Statman, 2000).

The earnings announcement drift and forward discount puzzle are effects of the anchoring heuristic. Since analyst often base their valuations on industry multiples, they use anchoring on a daily basis. Valuations are also calculated by using the current stock price as an anchor and then adjust according to expectation.

3.3.4 Representativeness

Since agents are only capable of handling a certain amount of information at the same time, the brain sometimes takes shortcut when making decisions. One of these shortcuts is representativeness and could be refers to as decisions based on stereotypes (Nofsinger, 2011).

One example of representativeness is the coin-toss; Shefrin (2001) found that people believe that H(ead)T(ail)HTHTHT is more likely than HHHHHHHH, since the first series exhibits perfect distribution. This result is in line with sample size bias, where people believe that even small samples should represent a fair distribution.

In the stock market, investors seem to overestimates the earning of good companies, driving up the stock price purely on information from the past, and at the same time confusing good stocks and good companies. More professional fund managers can utilize this anomaly by trading on a momentum strategy and by identifying companies with low price relative to their fundamentals. Since representativeness is present in the market, investor and analyst may also see the extremity of forecast being adjusted (Ganzach, 1998).

3.3.5 Conservatism

Montier (2002) argues that conservatism is the tendency to stick with a position, causing movement to be very slowly. It can be explained as a psychological explanation for the disposition effect. Conservatism leads to under-reactions regarding events, such as profit-warnings, and in contrast to representativeness, the investors are not able to adjust according to the new information.

Edwards (1968) and further Barberis and Thaler (2002) showed that if the data is not showing any clear representativeness or correspondence with a model, then people tend to under-react to the information and rely much on prior knowledge. Professional fund managers can utilize this anomaly by reacting faster to new information making and by finding unpopular stocks that have seen a decline in the price by being unattractive.

3.3.6 Mental accounting

Thaler (1999) defines mental accounting as operations of "*organize, evaluate and keep track of financial decisions*". The fact that people have different accounts in their head when evaluating decisions is called narrow framing, or mental accounting. People divide their current and future funds into different non-transferable portions or “silo” and then assigned different utility-levels to each account.

The important part of mental accounting is the opening and closing of different “silos” or accounts. Opening an account is when money is sorted into a silo, like investments or savings. These types of accounts are rarely closed. Closing happens when something paid in advance is consumed, like a vacation or a movie ticket. Most people do not set up different bank account for grocery shopping, entertainment or a new TV, but due to mental accounting the funds are kept separated. Under this regime, mental accounting can encourage people to be more economical and save more, since funds are kept apart in silos and set budget constraints (Ackert & Deaves, 2010).

3.3.7 PROSPECT THEORY

On basic assumption under behavioral finance is the violation of rational agents. In 1979 psychologists Kahneman and Tversky presented their prospect theory in an attempt to develop a new value function that explains decision-making under risk. The article gathered massive attention, and is still one of the most cited papers ever written in *Econometrica.* Since the article was presented in 1979, behavioral finance has taken huge steps in the right direction, trying to succeed the efficient market hypothesis as the best model for estimating security prices. Both Kahneman and Tversky have contributed massively to develop even better models, trying to explain how psychics affect business decisions. However, behavioral finance has not been able to develop a unified mathematical framework to explain all variation in security prices.

Prospect theory has ever since it was presented, been used as a foundation in the critique against the efficient market hypothesis. The theory reveals several results regarding inconsistency when faced with decisions under risk. The efficient market hypothesis suggests that investors are basing their decisions on expected utility. However, many studies show that people systematically violate the expected utility theory (Barber & Odean, 1998; Summers & Duxbury, 2007). Barberis and Thaler (2002) argue that violations of the expected utility theory can explain some financial phenomena present in the market, but all of them.

To quantify the prospect theory, Kahneman and Tversky (1979) used several experiments to understand the choices being made by agents, faced with decisions under risk.

One experiment was to ask agents to choose between different gambles with different outcomes, but with the same final wealth.

One of these gambles were asked the following way:

"*In addition to whatever you own, you have been given 1000 dollars. Now choose between A and B.*"

A: 1000 dollars with a probability of 0.5

B: 500 dollars for sure.

In this case, B was the most popular choice.

Then the same subjects were asked:

"In addition to whatever you own, you have been given 1000 dollars. Now choose between C and D"

C: -1000 dollars with probability 0.5

D: -500 dollars for sure.

Now the answer C was most popular.

Since the final wealth is the same in both gambles, there is a violation of the expected utility theory. According to expected utility theory, agents who choose B should also answer D. However, this reveals the core of the prospect theory; the non-linear value function.

By examining different variation of such gambles, Kahneman and Tversky were able to conclude that agents define their total utility over gains and losses, rather than final wealth, and that probabilities are replaced by decision weights. Since decision weights are found to be lower than the corresponding probabilities, the agents are likely to be influenced by other factors than utility. Uncertainty and focus on the *change* of utility rather than total level of utility, are two factors that may influence the decisions.

For an investor faced with an investment opportunity, a gain of $1000 increases utility less than a loss of $1000 reduces it. This gives a non-linear relationship between stated probability and decision weights. Kahneman and Thaler illustrates this non-linear relationship with a game of Russian roulette:

"Would you pay as much to reduce the number of bullets from four to three as you would to reduce the number of bullets from one to zero?"

Most people answered that they would be willing to pay much more for a reduction of the probability of death from 1/6 to zero than for a reduction from 4/6 to 3/6." (Kahneman & Tversky, 1979)

Secondly, they found that people are risk averse for gains of moderate to high probability and losses of low probability, and risk seeking for gains of low probability and losses of moderate to high probability. This gives a value function that is defined on deviation from a reference point, and is normally concave for gains and convex for losses. The function is also steeper for losses than for gains.

The last part of the theory is the nonlinear probability transformation, which shows that small probabilities are overweighed. This means that people place more weight on a jump of 20% from 0.8 to 1 than a jump from 0.2 to 0.25. This has later been known as the "certainty effect" (Barberis & Thaler, 2002).

However, prospect theory is not perfect since it easy to find gambles with payments X and Y, where Y > X in all situations. This violates the prospect theory, and is why Kahneman and Thaler released a revision of the prospect theory in 1992 adjusting the theory to a cumulative level.

3.3.8 Disposition effect

As presented in section 3.3.7, prospect theory explained that most people have an "S-shaped" value-function that is defined over gains and losses, rather than total value. Since the value-function is linked to a reference point, people generally tend to be risk-averse. In this regard researchers claim that investors tend to sell over-performing stocks, and to hold on to under-performing stocks (Ferris et al., 1988; H. Shefrin & Statman, 1985). This effect is called disposition effect, and can easily be observed in the market. The most common comment by private investors is perhaps, "the stock has gone up, I better sell to realize the gain" or "the stock has gone down, but the money is not lost until I sell the stock". This comment clearly shows the disposition effect.

Shefrin and Statman (1985) explain the disposition effect by prospect theory and regret aversion. Considering the value function of prospect theory, it is easy to see why people tend to sell winners. After a large gain of value, you are risk-averse and thereby thinking on how to sustain the value. On the other side, after a loss, you have moved to the risk-seeking part of the value-function, and thereby stick with the position. They also found that investors feel regret when closing a position due to a bad investment decision, and pride when the closing of a position resulting in a profit.

Odean (1998) observed 10.000 trading records and clearly found that people keep losers and sell winners. Odean tried to explain these observations with timing effects and rebalancing, but found nothing to support these hypotheses.

More recent studies (Barberis & Xiong, 2009; Summers & Duxbury, 2007; Weber & Camerer, 1998) also show that emotions have a great influence on the investment decision. By using a two-period version of the prospect theory, it is clear that the first decision to buy the stock would influence how the investors feels about the investment; If the investors have picked the stocks themselves, the regret and rejoice will be stronger than if the stock are picked by other. This means that if the investor is responsible for the outcome, both if it is a loss or a gain, the investor will show a disposition effect.

3.3.9 AVAILABILITY HEURISTIC

Studies show that current available information is used as a base when investors make their investment decisions. This leads to a situation where an event that is easy to remember is given a higher probability (Tversky & Kahneman, 1973).

Having a clever stock ticker is found to giving returns higher than the market (Head et al., 2009). This indicates that investors use information that is easy to remember, and is available when taking their decisions. Publicity from media will also affect the trading activity, and companies with easy names are found to perform better than market, especially right after public listing (Alter & Oppenheimer, 2006).

3.4 Implications for stock prices

Through empirical studies of individual stocks, researchers have found that some groups of stocks can earn higher than average returns. These abnormal returns are often linked to under- and overreactions made by investors. Scholars from the rational approach and the behavioral approach have different explanations for these cross-sectional returns; Fama (1997) argues that the different anomalies are rational, and adds support to the theory about efficient market. He suggests the anomalies being chance results, and that overreaction and under-reaction is equally common. He further finds that most of the long-term anomalies are fragile and tend to disappear with changes in the way they are measured (Fama, 1997).

In contrast, Daniel et al. (2004) argues that these cross-sectional returns are a result of investor behavior. They suggest that overconfidence among investors implies an overreaction to private information and under-reaction to public information. They also suggest that investors have different confidence based on the outcome of their decision.

In this section some of the most known anomalies, or cross-sectional stock returns, are described.

3.4.1 The size and value premium

By sorting stocks into deciles based in their size Banz (1981) and Fama and French (1992) found that smaller firms have higher risk adjusted returns than the market. Fama and French (1992) studied the period from 1963-1990, and used data on all stocks listed on NYSE, AMEX and NASDAQ. Each stock was sorted into deciles based on their market value, and return in each declie was calculated. Their study found that the smallest stocks quintile yield a 0.74% higher return than the large-stock quintile each month.

More recent studies in the German-, Taiwan- and the UK market, confirms the existence of the size-anomaly in the market. (Amel-Zadeh, 2010; Y.-S. Huang, 1997; Levis, 1989). However, due to the increase of institutional investor in the market in the later years, the size-premium seems to have been reduced (Banz, 1981; Fama & French, 1992; Gompers & Metrick, 2001).

Fama and French (1992) also found that stocks with high book-to-market ratio, value stocks, had higher returns than stock with low book-to-market ratio.

Under the rational approach, Fama and French (1992) suggest the value premium could be seen as a risk factor. They argue that risk related to stock returns is multidimensional, and that one risk factor is the book-to-market ratio. This risk factor may be considered as the relative distress factor observed by Chan and Chen (1991), indicating that stocks with high book-to-market ratio are more vulnerable to financial distress.

The behavioral approach to asset pricing has a different explanation for the size premium; Skinner and Sloan (1999) argue that the size premium is present due to earning shocks. Their findings indicate that most of the realized value premium is a result of stock prices adjusting after earnings surprises, rather than the expected risk premium. The value premium will be futher disused in section 4.2

3.4.2 MOMENTUM

Momentum is the anomaly where returns are positive correlated with previous returns. This is in contrast to reversal where returns are negative correlated with previous returns. De Bondt and Thaler (1985) found that over a holding period of 3-5 years, stocks with poor performance in the prior 3-5 year, outperformed the stocks with better prior performance. They argue that momentum is due to overreaction in the market, making the extreme losers cheap and thereby bounce back, whereas as the extreme winners become too expensive and fall back. De Bondt and Thaler also argues for a long-time reversal of the momentum factor, indicating that over a long time-period prior winner become losers. Jegadeesh and Titman (1993) further studied the momentum factor in the short run. By sorting all stocks from 1963 to 1989 on NYSE into deciles based on their six-month prior performance, found that the prior winners outperformed prior losers by 10% on an annual basis. The stock performing best was no more risky than the worst performing. They argue that the momentum anomaly is due to under-reaction by investors to the release of firm-specific information, which indicates a cognitive bias. The length on the prior ranking period has an important influence on the results, and Jegadeesh and Titman (1993) found different results when they used different time periods (Bondt & Thaler, 1985; Jegadeesh & Titman, 1993).

Using the Fama-French three factor model, Fama and French (1992) tried to give a rational explanation for the momentum anomaly However, their result indicates that the three-factor model is not able to explain the short-time momentum strategy, since all of the intercepts are positive for short-term winners (La Porta et al., 1995).

3.4.3 52-WEEK HIGH ANOMALY

Another momentum strategy is the 52-week high strategy. By calculating the ratio between a stock's current stock prices and it's past 52-week high price, stocks are determined to be either winner or losers. By constructing a zero-investment portfolio consisting of long-winners and short-losers, George and Hwang (2004) created a 52-week high strategy yielding 0.45% return in the US stock market.

They also found, in contrast Jegadeesh and Titman, (1993), that long-time revarsal do not occure. Further, they showed that nearness to the 52-week high is a better predictor of future returns than past returns. This indicates that the price-levels are more important than previous price changes. (George & Hwang, 2004). A more recent study also finds the 52-week high anomaly in nine out of thirteen stock markets, with average monthly returns of 0.6% to 1.0% (M. Liu et al., 2011).

3.4.4 POST-EARNINGS ANNOUNCEMENT DRIFT

The post-earnings announcement drift is observed by using event studies, to understand how the stock-price reacts to earnings announcement. This method is used to compare companies over event-time rather than calendar-time. To study this anomaly, researcher divide the stock into deciles based on the earning-announcement, from extremely positive to extremely negative. Based on the deviation from the expected announcement, scaled by volatility, they found that stocks with the biggest surprise outperformed the market by over 2%. Different studies find the anomaly in both in the US and the UK market, and even if the surprise is measured relative to analysts' expectations, the anomaly is present (Bernard & Thomas, 1989; L. K. Chan et al., 1995; W. Liu et al., 2000).

The post-earnings announcement drift anomaly violates the efficient market hypothesis since a speculative profit would remain, even after transaction cost. The most accepted explanation for the anomaly is the under-estimation of earnings-announcement made by investor. The post-earnings-announcement drift is one of the most accepted anomalies in the market, and even Eugene Fama accept this anomaly to be present and robust (Fama, 1997).

3.4.5 SEASONALITY EFFECT

Studies of stock-returns consistently show that returns on stocks are higher at some days of the week, at some times of the week or even in some specific months of the year. The different anomalies are found in stocks, treasure bills, debt and even exchange rates.

DAY-OF THE-WEEK EFFECT

Research shows that weekdays have influence on the expected stock return. Several studies prove that returns on Mondays are found to be abnormal negative, which is referred to as the weekend-effect. While Fama (1980) found abnormal positive returns on Mondays, more recent studies have shown abnormal negative returns on Monday and abnormal positive returns on Fridays. A rather new study found that the day-of-the-week effect is a rolling term, and the statically Monday and Friday effect has disappeared. However, they clearly find a weekday-effect, but it wanders between a random walk and a fixed weekday effect (Doyle & Chen, 2009). In his study of empirics on the Oslo Stock Exchange, Ødegaard (2010) finds Fridays having the best daily average returns (0.14 daily return), while Monday had lowest returns (0.02 daily return), clearly in line with international studies.

MONTH EFFECT

Wachtel (1942) was first to observe the January-effect, which suggests a higher realized return in January, than in the rest of the year. However, this does not imply that taking a long position in January and neutral or short in rest of the year would yield any excess return. Some market participants argue that this anomaly have disappeared the recent years, while some studies still find evidence of higher returns in January (Haug & Hirschey, 2006). There is also evidence of that the period from May to October yield less return than October to May. The same effect in present the Norwegian market, with January having the highest average a monthly return of 3.9%, and September the lowest average a monthly return -0.2% (Ødegaard, 2010)

3.4.6 Affect

Statman et al. (2008) showed that investors prefer stock with positive effect, where effect is defined as the quality of "goodness" or "badness". The investors' preferences drive up the price on the stocks with positive affect, lowering the returns. After controlling for the market, size, style and momentum the stocks with negative affect still generate an alpha of 2% per annum (Statman et al., 2008).

3.5 IMPLICATIONS FOR PORTFOLIO MANAGEMENT

Under both the rational approach and the behavioral approach, fund managers are trying to beat the market. This is done trough active management of the fund.

By active fund management the fund manager is trying to generate excess returns above the return on a benchmark. To beat the market, the fund manager needs to have information or be skilled, and for this the manager is compensated. This means that active funds have much higher fees than index- and passive managed funds.

There is mainly two different ways the manager can beat the benchmark; market timing or stock-picking. Market timing is done by varying the exposure to different risk factor through bull- and bear-market. Stock-picking is done by underweighting or overweighting in particular securities relative to the benchmark.

Since an active fund is trying to outperform the market, it is required that the market is not semi-strong efficient, as defined in section 2.1. If the market were efficient, there would be no incentive for the fund manager to engage in the costly process of gathering information. This equilibrium is referred to as an "*equilibrium of degree of disequilibrium"* (Grossman & Stiglitz, 1980). In the Norwegian market, Sørensen (2009) argues that since Oslo Stock Exchang is a small market, professional mutual fund managers are more likely to do well, based on the notion that inefficiency is more likely to be present in a small market. Following that argument, by investigating mutual fund performance on Oslo Stock Exchange, one could also test the level of efficiency in the market.

In the context of behavioral finance, Shefrin and Statman (2002) developed a way to construct optimal portfolios when taking mental accounting into consideration, and compared it to the mean-variance optimal portfolio. They suggest that the behavioral portfolio should be created using a pyramid structure, including risky assets at the top level, and less risky assets at lower level. They further argue that the behavioral portfolio consist of both safe investments, and investments which can be categorized as lottery tickets (H. M. Shefrin & Statman, 2002). Curtis (2004) builds further on the work of Shefrin and Statman (2002) and combines the mean-variance portfolio and the behavioral portfolio, in order to create the best portfolio for the investor. He argues that the investor may start out with a behavioral portfolio, and then converge toward the mean-variance optimal portfolio in order to obtain the optimal portfolio for the investor.

4.0 MUTUAL FUND INVESTING AND PERFORMANCE

In this section 4.1 a short review of different studied concerning mutual fund inventing is presented. Section 4.2 conations a discussion on the difference between behavioral and rational portfolio management. Section 4.3 concerns the issue of value investing, whereas sections 4.4 introduce the Norwegian fund market.

4.1 MUTUAL FUND PERFORMANCE

Numerous studies have been conducted in order to test the performance of active managed funds. Jensen conducted one of the first studies, in 1968. He studied 115 mutual funds and their performance in the period from 1945 to 1964. Using the single index model, Jensen found that on average active funds earned about 1.1% less per year than they should considering their level of systematic risk. He did only find small evidence that any individual fund was able to do significantly better than expected from mere random chance. Jensen finds similar results both at gross and net level, which indicates that active managed funds were not successful enough to cover up the broker expenses (Jensen, 1968).

As mention in section 2.4, Fama and French (1992) introduce the Fama and French three-factor model to capture market behaviour. This model is an extended version of the CAPM developed by Sharpe (1964), Lintner (1965) and Mossin (1966), and the model captures the risk-variables related to size and market capitalization. The purpose of their study in 1992 was to given a better explanation for the cross-section of expected stock returns. In 2008 Fama and French applies their model developed in 1992, in order to test mutual fund performance. They start out from the perspective of equilibrium, and examine mutual funds at the aggregate level. Their findings show that the mutual fund industry, as a whole, holds a portfolio much like the market portfolio. Using the three-factor model of Fama and French (1992) the study reports negative alpha values on the net level. Over the total time period, the equally weighted portfolio delivers an annualized gross return of 0.61%, but at the net level the annualized returns are -0.52%. This indicates that on the aggregate level, active managed mutual funds has not been able to deliver abnormal return to the investor after controlling for risk related to the three factor portfolios, and deducting costs. Their results further suggest that the cross-section of average fund returns is a result of randomness, rather than skill. The result of Fama and French supports the findings of both Jensen (1968) and Carhart (1997)

Carhart (1997) also performed a study on mutual fund performance. Using a survivorship-bias-free dataset, he studied 1892 mutual funds in the time period from 1962 to 1992. His study for persistence in fund performance was conducted using the singe-index model and the Carhart four-factor model. To examine short-time persistence, all funds are sorted into ten equally weighted portfolios using reported returns. The portfolios are held for one year before they are reformed. Carhart reports that holding the top decile over the total time period yield a monthly excess return of 0.68%. In contrast, holding the bottom decile yield only a monthly excess return of 0.01%. Carhart's results also indicated that the single-index model is no able to explain the relative return on these portfolios, since the top decile and the bottom declie has almost the same beta coefficient. Using the Carhart model explains more of the spread and pattern in these portfolios, and he reports that most of the difference in performance can be explained by the sensitivity to small stock and to momentum. However, none of the deciles are able to deliver positive alpha under the four-factor model. To test for long time persistence the funds are ranked according to their alpha estimated over the prior 3-years. Using this method, Carhart reports that the strategy of buying the top declie and selling the bottom declie would yield a return on 8% per year. He argues that most of this spread is due to market value and the momentum factor. Carhart concludes that only fund in the top decile are able to earn back their investments expenses both in the short- and long-run, but most funds are underperforming about the size of their investment cost (Carhart, 1997).

To test whether behavioral finance has practical application for mutual funds, Reinhart and Brennan (2007) studied the performance of nine mutual funds that claim to use behavioral finance in their investments strategy. Using the CAPM they calculated the Jensen's alpha, information ratio and the Treynor ratio. Their results indicate that, on a risk-adjusted level, large-cap behavioral funds preformed considerable better than small-cap, value and growth behavioral funds, and also outperformed their respective Morningstar and Lipper indices. The information ratio supports these findings, though growth fund outperformed large-cap under the information ratio. Their overall conclusion is that behavioral funds investing in large-capitalized securities take best advantage of behavioral factors. Reinhart and Brennan argues this is a result of large-capitalized securities being highly liquid, well known for many investors, followed in the media a therefore vulnerable to irrational investors.

Wright et al (2006) further expand the literature on behavioral fund performance by studying the performance of 16 behavioral mutual funds. They define behavioral mutual fund as funds that claims to base their investments strategy on principles of behavioral finance. Their study examine whether the funds are profiting from the doctrine. By using different variations of the Carhart four-factor model they measure the performance both individual for each funds, and for an equally weighted portfolio. Their results indicated that behavioral mutual funds are successfully attracting investment dollar. They also find the funds outperforming S&P 500 index funds, and to some extend outperform non-behavioral funds on a non-risk-adjusted level. They further suggest this ability to beat the S&P 500 index funds is a function of relative high loading on the HML factor from the Fama and French model in times when the realization on this factor was high. However, they conclude that behavioral mutual funds have not been able to deliver any abnormal return outside the four factors of the Carhart model. They also find the funds not being able to time their loading on the realization on the four factors from the Carhart model. This leads to their conclusion that behavioral finance is not much more than value investing.

Compared to the number of studies of the US market, only a few studies concerning the Norwegian fund market have been conducted. Gjerde and Sættem (1991) was one the first studies on Norwegian mutual fund performance. Their study involved 14 mutual funds in the time period from 1982 to 1990. When analyzing the systematic risk related to the funds, their results indicates that funds from the same management had almost similar risk profiles, while comparing risk profiles between management companies showed significant differences. They results further suggests that some of the fund managers had the ability to time the market, but managers were not able to outperform the market index benchmark at a risk-adjusted level.

Sørensen (2009) conducted the most comprehensive study of mutual fund performance in the Norwegian market. He studied mutual fund performance by using a dataset free of survivorship-bias over the time period from 1982 to 2008 and applied the Fama and French (1992) model to analyze the risk-adjusted performance. The results show little evidence of funds being able to produce any risk-adjusted excess returns compared to the benchmark returns. The study further indicates that looking at prior performance is not a good predictor of future performance, since there is no evidence of persistence performance among the funds. Sørensen do find some funds performing well in terms of actual returns, but he suggests this is a result of the funds taking on risk systematic risk measured by beta. Sørensen sums up his study by concluding that his data adds support to the famous thesis about a blindfolded monkey throwing darts at Wall Street Journal to select a portfolio, would do just as well as a carefully selected portfolio (Reinhart & Brennan, 2007). He further suggests that the best investment decision is to buy a broad index fund with low expenses.

4.2 Behavioral versus rational portfolio management

Portfolio management can in general be divided between active and passive management. As presented in section 2.7, the rational approach suggests that the optimal portfolio consist of a combination of the risk-free rate and the market portfolio. In contrast, the behavioral approach to portfolio management suggests that the fund should be active managed and utilize some of the anomalies created by psychology. The topic of active fund management is still under discussion, though most of the later studies report that active managed funds are not able to outperform the market on a risk-adjusted level (Sørensen, 2009; Tveito, 2006; Wermers, 2000). Studies of behavioral mutual funds indicate that funds following a behavioral strategy are able to outperform index funds, but not earn risk-adjusted abnormal returns (J. C. Huang et al., 2010; Wright, et al., 2006). Regarding the discussion of passive versus active portfolio management, the study of Wright et al. (2006) could indicate that active portfolio management is earning better returns for the investor. Other studies indicate that active managed funds with a consistent strategy are in fact able to outperform funds with a shifting strategy. One can also argue that passive management is better when the market holds a high degree of efficiency, like the US market (Chen & Zhao, 2009).

4.3 Value investing

One on the main discussions between the supporters of behavioral finance and supporters of the efficient market hypothesis is the case of value investing. Value investing can be defined as investing in stocks with high book-to-market ratio in order to capitalize on the value premium. The value premium has been given a brief introduction in section 3.4.1, however, in this section the different explanations for the presence of the value premium is discussed.

The rational approach to explaining the value premium is to assign a risk factor to value stocks in order to explain the relative higher return. After examining stock returns, and finding the value premium to be present, Fama and French (1992) attribute the high return of value stocks to the distress factor observed by Chan and Chen (1991). This is further studied by Fama and French (1998). Using international data, they observed that a portfolio of value stocks outperformed a portfolio of growth stocks by 7.68% per year in the time period 1975-1995. They suggest that adding a risk factor related to relative distress in the APT developed by Ross (1976) or the intertemporal capital asset pricing model (ICAPM) of Merton (1973) captures the value premium. Liew and Vassalou (1999) tried to explain the relative high return on value stocks by linking the HML portfolio to future economical growth. Their study adds support to the view of Fama and French since returns on the HML portfolio is positive correlated to further economical growth. They conclude that a risk-based explanation is plausible and likely, since HML can be considered a state variable that predict future changes in investments opportunity set.

Zhang (2005) adds further support to the rational explanation for the value premium. His explanation relies on two assumptions; Costly reversibility and countercyclical price of risk. Under these assumptions, Zhang argues that value stocks are burden with capital that is unproductive during bad times. This implies that growth stocks are more capable of adjusting their capital base in order to always stay productive, and thus value stocks must be associated with risk related to distress. He further argues that reducing the capital in place is harder than reducing the new investments, causing value stocks to be more risky than growth stocks.

The unified explanation for the value premium under the rational approach is risk related to distress. All of the studies laid out above conclude that value stocks are more risky, and thereby have higher returns relative to growth stocks, causing the value premium to be present in the market.

The behavioral explanation for the value premium is based on misjudgment by investors. Lakonishok et al. (1994) argues in their study that value premium is a result of "*noise traders extrapolation past information too far into the future*". They suggest that investors buy up growth stocks making them pricy, and thus reducing the return to the investor. The buy-up is done on prior information about growth, and the hope that growth will continue, are increasing the price. Lakonishok et al. further argues that the market overestimates future growth rates of glamour stock, relative to value stocks, and in contrast to Fama and French (1992) they find value stocks not being more risky than growth stocks in terms of fundamental risk. To conclude their study, they suggest that the value premium is present in the market since both individual and institutional investors seems to prefer glamour stocks and avoid value stocks. The reason for this is the history of growth stock, having a higher growth rate that value stocks. There also seems to be misjudgment that good companies are good stocks. The last suggestion presented by Lakonishok et al. is that short time horizon may favor growth stocks compared to value stocks, since not all investors have the long time horizon on the investment.

In a more recent study, Skinner and Sloan (1999) examined growth and value stocks around earnings announcements. They found that growth stocks delivering results short of the expectations fell significantly more that value stocks that missed the expectations. The difference was 9%, with growth stocks falling 15% and value stocks falling 6% after missing the expectations by 5%. They attribute the large negative reaction in growth stocks to the fact that investors buying growth stocks are expecting the growth to continue, and thus the relative negative reaction will be larger. This supports the study of Lakonishok et al. (1994) that investors overestimate future growth rates based on history.

James Montier is a behavioral analyst. He sums up his two books on value and behavioral investing, that value investing is caused by behavioral biases (Montier, 2007, 2009). He argues that value investing is the only method that has been able to deliver sustainable returns over a long time period. By citing multiple studies, Montier explains why the efficient market hypothesis is not relevant, and why the modern portfolio theory is outdated. Montier also adds support to the value strategy of Benjamin Graham and Warren Buffet. In the article "The Superinvestors of Graham-and Dodd" Buffet refuse the efficient market hypothesis, and states that some fund managers are actually able to outperform the market by following the value strategy. This adds support to the argument about the difference between price and value being a result of irrational investors in the market, and not related to risk (Buffett, 1984).

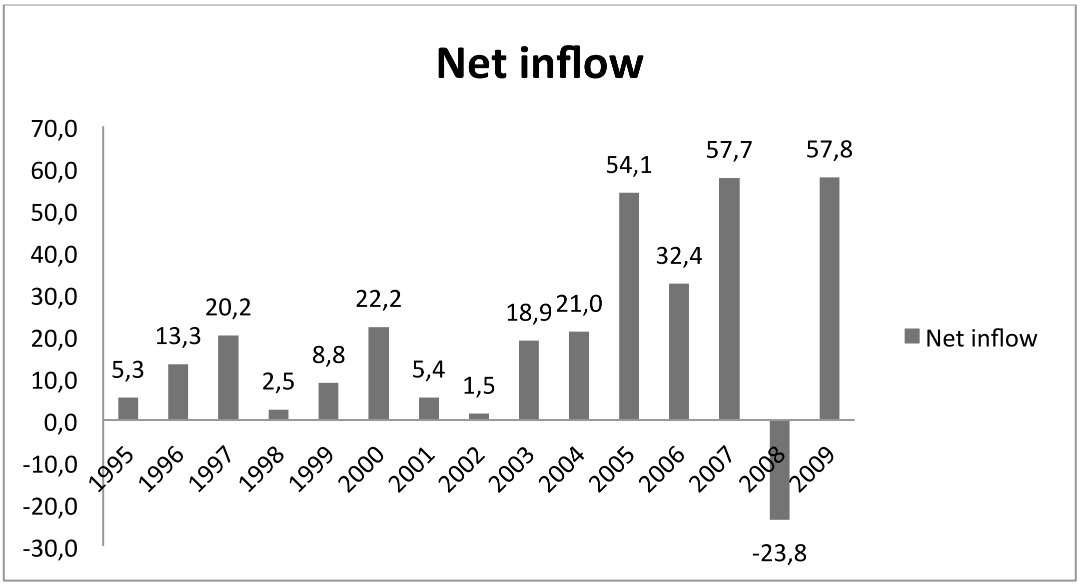
Even though there is a common knowledge that the value premium exists in the market, researchers still argue why the anomaly is present (Fama & French, 1996; Gompers & Metrick, 2001; La Porta, et al., 1995). As discussed in this section, the rational and the behavioral approach offer different explanations: the rational approach considers value stocks more risky, whereas the behavioral explanation is that value stocks have higher returns as a result of irrational investors. This also causes problems when evaluating value funds. Some value funds may consider the value premium being a result of distress risk, while other may consider the value strategy being a behavioral strategy. However, since the question still remains unsolved, the value premium must the interpreted by the each investor according to his conviction.

4.4 The Norwegian fund market

The majority of funds in the Norway market are active-traded and open-end funds. From the first funds was established around 1982 and until today, the Norwegian fund industry has seen a large development both in capital under management and the number of funds.

The first tests of performance in the Norwegian fund market report that the market value was only around 290 million NOK in 1982 (Gjerde & Sættem, 1991). After the significant growth in matter of numbers of Norwegian mutual funds during the 1980 and 1980, there has been a reversal in the years after 2000. However, the fund-market as a whole has been steadily increasing also after year 2000. Is also seems to be a shift from funds with a Norwegian mandate, to funds with a more international mandate. While 92% of capital in 1994 was invested in funds with a Norwegian mandate, this share has decreased steadily and was less than 20% by the end of 2008. Asset under management was reported to be around 50 billion NOK in 2007, a number which was almost halved during the financial crises of 2008, due to large negative return (Sørensen, 2009).

FIGURE 1: NET INFLOW IN NORWEGIAN MUTUAL FUNDS 1995-2009



The figure displays the net inflow into Norwegian mutual funds . Year is denoted on the horizontal-axis and billion NOK on vertical-axis. (Source: Norwegian Fund and asset management association, www.vff.no)

5.0 SELECTION OF FUNDS AND DATA SAMPLE

This section presents the data sample gathered and selection of funds that lays the foundation for the empirical result in section 6. Section 5.1 presents the selection of funds and the comparison tools applied when analyzing the empirical results. Section 5.2 gives a brief review of the data sample and presents the regression models applied.

5.1 SELECTION OF FUNDS

In order to recognize behavioral mutual funds in the Norwegian market, the funds are categorized based on the written statement in which the fund manager induces to utilize "behavioral finance" to make investment decisions, a methodology also adapted by Reinhart and Brennan (2007), and Wright et al. (2006). Unlike the fund managers in the US market, none of the fund managers in the Norwegian market explicitly admits make investments based on behavioral finance. As discussed in section 2, 3 and 4, this means defining what makes a mutual fund behavioral involves subjectivity; some funds are clearly not trying to utilize known anomalies and rely only on different quantitative analysis, while others use behavioral finance to some extent. Though funds have different strategies, behavioral finance is generally trying to profit from errors made by the investor at the aggregate level.

A detailed and comprehensive review of 67 prospectuses of Norwegian funds, published on the Morningstar and the fund manager's website, is done in order to familiarize behavioral mutual funds in the Norwegian market. Based on the prospectus of funds and about the investment philosophy of the different fund companies, I try to match their strategy with anomalies caused by either limits to arbitrage or psychology. As earlier noted, all active fund managers are trying to outperform the market, indicating that all funds violate the efficient market hypothesis. This could be an argument for inclusion of all active managed funds in the dataset, thus categorizing all active funds as behavioral. However, by reading prospectuses I find some funds clearly using already known cross-sectional average returns in their strategy, while other may try to utilize the anomalies created by behavioral anomalies. Inclusion of all funds will thus be a mix of conventional funds betting on luck and timing, whereas the behavioral funds follows a strategy involving anomalies created by behavioral finance.

As discussed in section 3, there exist some well-known anomalies in the stock market that may be utilized by mutual funds. These anomalies, among others, include representativeness

(Ganzach, 1998), conservatism (Montier, 2002) prospect theory (Kahneman and Tversky, 1979) and momentum (Jegadeesh and Titman, 1993). These characteristics lay the foundation of the selection of funds in the empirical analysis in this thesis.

Based on the mutual fund investment philosophy, I have identified six funds in the Norwegian market that shows characteristics that might indicate applying a behavioral finance strategy. The strength of the characteristics varies between the selected funds. A more detailed review for inclusion of each specific fund is further discussed in section 5.2.1.

5.1.1 SURVIVORSHIP BIAS

The database consisting of 67 Norwegian mutual funds might contain survivorship bias, since only funds alive at the end of 2010 are included. Survivorship biases may have an impact on the empirical results, since bad performing funds are liquidated and removed. In this study, one cannot be sure that funds, which use behavioral finance, have not been liquidated. Sørensen (2009) reports survivorship biases in the Norwegian market, in the time frame 1982-2009, making an annual difference between all funds and surviving fund of 0.84%.

5.1.2 SELECTION BIAS

An issue for this study is selection bias. Since the funds are selected after a subjective analysis of the prospectus and investment profile, is it highly likely that some behavioral funds are neglected and not included in the sample. It is also likely that some of the funds included are not using behavioral finance as a part of their strategy. Another implication is the inclusion of some value funds, which makes the sample biased towards value investing. As discussed in section 4.3 the strategy of value investing could be considered both rational and behavioral. It is therefore important to remember the selection bias when analyzing the empirical results.

5.2 PRESENTATION OF SELECTED FUNDS

Using a dataset consisting of 67 Norwegian or Norwegian/International mutual funds, I have identified 6 funds that may use behavioral finance in their investment strategy. The dataset was provided by Oslo Stock Exchange and contains monthly net return calculated using arithmetic average after deducting fixed management costs from the net asset value.

In order to recognize behavioral mutual funds in the Norwegian market, the funds are categorized based on the written statement in which the fund manager induces to utilize “behavioral finance” to make investment decisions, as mentioned above. The Norwegian mutual fund managers' do not explicitly admits that they make investing decisions in contrast to mutual fund managers in the US market. Wright et al. (2006) identified 16 self-proclaimed or media-identified behavioral mutual funds, as they define, in the US market. As mutual fund managers in the Norwegian market do not explicitly have "behavioral" as a part of their fund names or directly quote the mutual funds as "behavioral", the data sample approach of Reinhart and Brennan (2007) and Wright et.al (2006) cannot directly be adapted in this study. Therefore, a similar approach to define the data sample is implemented. Table 1 gives an overview of the selected funds: Pareto Aksje Norge, Dephi Norge, PLUSS Aksje, Odin Norge, Skagen Vekst and Holberg Norge. The table also lists the fund management company. None of these managers explicitly admits that their funds are "behavioral" but their investment profile show similarities to behavioral funds. This is the foundation of the selection of funds and will be reviewed in detail in the fund sections below.

TABLE 1: DESCRIPTIVE DATA ON SELECTED FUNDS

Fund	Ticker	Manager	Inception date	Benchmark	Asset under management
Pareto Aksje Norge	PAA	Pareto Asset Management As	06.09.2001	OSEFX	NOK 6 905 mill.
Delphi Norge	DHN	Delphi Fondsforvaltning As	03.06.1994	OSEFX	NOK 858 mill.
Pluss Aksje	PLA	Fondsforvaltning As	01.12.1996	OSEFX	NOK 136 mill.
Odin Norge	ODN	Odin Forvaltning As	26.06.1992	OSEFX	NOK 6 127 mill.
Skagen Vekst	SKV	Skagen Forvaltning As	01.12.1993	OSEBX and MSCI AC (50/50)	NOK 10 230 mill.
Holberg Norge	HBN	Holberg Fondsforvaltning As	28.12.2000	OSEFX	NOK 2 612 mill

PARETO AKSJE NORGE

Following the investment strategy tought by Benjamin Graham and Warren Buffett, Pareto Forvaltning invests in solid companies with strong balance sheets, high equity ratio and high return on equity. The strategy imposes a long time horizon and their investment decisions are not influenced by short term "waves" in the market. Pareto Forvaltning has around 15 billion NOK in capital under management.

Started in 2001, Pareto Aksje Norge *"invests in companies listed on the Oslo Stock Exchange, Norway. With a value, long-only investment philosophy, we look for well managed companies with an understandable business model and transparency to risk-taking" (Forvaltning, 2010)*

The fund holds 6.9 billion NOK in asset under management and is benchmarked against OSEFX.

WHY BEHAVIORAL?

By picking value-stocks, the fund may try to capitalize on the relative high cross-sectional returns of stocks with high book-to-market value. This is can also be a way to capitalize on the anomalies of conservatism and representativeness, since small private investors react slowly to new information, and the fact that noise traders confuse good companies with good stocks. Pareto also states that they follow the value strategy laid out by Warren Buffet, which is said to be critical about the efficient market hypothesis. Buffett argues that the market contains inefficiency since herd behavior, greedy people or emotional persons can drive prices away from their fundamental value. While not riding the short term "waves", the fund can to some extend be regarded as behavioral, since they are comparing the fundamental value to the price. If irrational noise traders were not present in the market, the fundamental value and the stock price should be equal, not making such value investing profitable. The fact that Pareto follows Warren Buffett's strategy implies they are aware of noise traders in the market and are trying to capitalize on irrational market prices, perhaps created by different behavioral biases. Pareto can thus be categorized to have a behavioral approach to the value premium.

Delphi Norge

Delphi has an investment philosophy based on both fundamental analysis and trend analysis. While most of the active managed funds only use fundamental analysis, the edge for Delphi is also the use of trend analysis. This way of utilizing momentum in the market makes them able to capture trends, and to increase their ability to time and select the correct investments (Fondene, 2011a).

Established in 1994, Delphi Norge invests in Norwegian stocks. By selecting 3-5 stocks divided between minimum 5 sectors, the focus is to identify stock showing strong momentum yielding potential high short-term returns. The fund has NOK 858 mill in capital under management and is benchmarked against OSEFX.

WHY BEHAVIORAL?

The prospectus of Delphi Norge indicates that the fund is trying to capitalize on the momentum factor using trend analysis. Using the momentum factor to capture drift in stock prices may be considered as trying to utilize the effect of herd behavior in the stock market. As laid out in section 3.4.2, Jegadeesh and Titman (1993) argues that in the short run, prior winner continue to outperform prior losers. Their study found that momentum factor being present in the market due psychological elements. Knowing that momentum is a profitable strategy, Delphi Norge may try to capture the short time trend caused by irrational investors, which is similar to a behavioral finance strategy (Fondene, 2011b).

PLUSS AKSJE

The mutual fund manager of PLUSS Aksje, Fondsforvaltning AS, focus mainly on fundamental analysis, but also analyze external factors such as macro events, political stability and demographic features when making investments decisions (Fondsforvaltning, 2011a)

The fund was established in December 1996 and invests primarily in stocks listed on the Norwegian stock market. 20% of the capital may be invested in the global market. The fund has a relative free mandate and can be considered as a stock-picking fund with long investment horizon, and is benchmarked against OSEFX (Fondsforvaltning, 2011b).

WHY BEHAVIORAL?

The fund has a relative free mandate and picks stocks according to their expectations. This also means being style-neutral both in term of segments and relative to the index. By using stock picking as their strategy, it may be assumed they are trying to capitalize on some of the anomalies created by psychology in the market.

One could argue that the fund is a conventional active managed fund, but by reading the prospectus, I would argue that the free mandate give the fund manager an edge in the market utilizing opportunities perhaps created by behavioral biases. This fund does not have as strongly characteristics as Delphi Norge, but there are some similarities relative to funds not having any similarities, and is therefore included. The prospectus also list a higher than average Sharpe Ratio, which indicates less diversification and higher risk.

ODIN NORGE

ODIN Forvaltning has become one of the largest fund managers in the Norwegian market. Their investment approach is to identify companies that reflect popular products, strong cash flow, solid balance sheet and high dividends. Their main approach is to find undervalued firms in the stock market (OdinFondene, 2011b). In 1992 ODIN Norge was established. The fund has more than six billons NOK in capital under management, and is benchmarked against OSEFX (OdinFondene, 2011a).

WHY BEHAVIORAL?

According to ODIN Norge's investing prospectus the fund manager describe their investment strategy as a continuous search of undervalued stocks under a free mandate. ODIN Forvaltning AS makes the following statement about their investment strategy: "*Our starting point is that it always exists mispriced stocks, and a portfolio of undervalues companies will provide excess return over time*" (Nils Petter Hollekim). Odin is aware of the presence of noise traders in the market, which indicates that they search for investment opportunities where they can capitalize on the noise traders. ODIN Norges's approach of utilizing investment opportunities based on mispriced and undervalued stocks, is similar to the characteristics of behavioral mutual funds. ODIN Forvaltning further makes the following statement: "*The knowledge of stock market psychology may reduce the likelihood of mistakes. By taking advantage of a fund manager like ODIN, with long experience in the stock market, places a good foundation for the success of your long term saving*". This statement indicates that they include market psychology in their investment decisions, which reflects a behavioral strategy approach, though they are not explicitly indicating or directly admits that they are assessing a behavioral strategy. Compared to the other funds in the Norwegian market, ODIN Norges approach is not necessarily a behavioral fund but has a stronger resemblance with respect to a behavioral strategy. ODIN Norge is therefore on this basis included in the selection of funds.

Skagen Vekst

Skagene Fondene is a Stavanger based investment management company with three mutual funds and four bond funds. Founded in 1992, with the first fund being launched in 1993, Skagen has become one of the largest fund managers in the Norwegian market with over 100 billion NOK under management. Inspired by Benjamin Graham, Skagen Fondene is using a value-based and active investment strategy to earn excess return for the investor (SkagenFondene, 2011b). Skagen Fondene incepted the mutual fund Skagen Vekst in 1994 and has a main goal of identifying companies that are undervalued, under-researched, unpopular and using common sense with a broad mandate over a long time horizon, the fund managers tries to provide the best risk-adjusted return for the clients (SkagenFondene, 2011a).

WHY BEHAVIORAL?

According to Skagen Vekst's investing prospectus they have an explicit strategy to invest in undervalued, under-researched and unpopular stocks. This strategy may indicate that Skagen Vekst does not consider the market efficient, and thus accepts the presents of irrational noise traders in the market. This acceptance could be used in their favor by utilizing some of the anomalies created by psychology.

By continuously trying to capitalize on undervalued, under-research and unpopular stocks, Skagen Vekst is similar to the utilization of the behavioral anomalies of representativeness and conservatism in making investments opportunities. As mentioned in section 3.3.4, the anomaly of representativeness refers to the fact that investor based their decision on stereotypes. The anomaly can create attractive investments opportunities to Skagen since they focus on under-researched companies. By formulating an explicit strategy about unpopular stocks, Skagen Vekst might also use the argument about affect for investing in unpopular stocks is as laid out in section 3.4.6.

Based on the investigation of Skagen Vekst prospectus, their investing profile is more strongly related to the behavioral anomalies. Similar to the mutual fund managers in ODIN Norge, the fund managers in Skagen Vekst do not explicitly admits that they are using a behavioral strategy, though they are using an approach related to the anomaly representativeness which indicates a behavioral strategy. Compared to ODIN Norge, Skagen Vekst reflects stronger similarities to a behavioral strategy than ODIN Norge, though none of them directly quotes to a behavioral strategy. Skagen Vekst is therefore also included in the selection of funds.

HOLBERG NORGE

Holberg Fondene is a fund management company based in Bergen, and was established in 2000. The company is partly owned by partners, which secures stability and continuity among key personnel. The company is trying to be the preferred niche player in the fund management market, by achieving competitive returns and high focus on client communication (HolbergFondene, 2011b).

Started 28.12.2000, Holberg Norge invests in stocks and equity certificates listed on Oslo Stock Exchange. The fund has NOK 2.612 mill in capital under management, and up to 20% of this amount can be invested abroad. The fund use OSEFX as benchmark index (HolbergFondene, 2011a).

WHY BEHAVIORAL?

According to the Holberg Fondene's investing prospectus, they do not believe in efficient market and see attractive investments opportunities created by irrational markets and "black swans" which may indicate that the fund managers also focus on mispriced stocks. As a style-neutral and professional stock-picker, the fund managers are freely to choose the stocks they like, and not only the ones included in the benchmark index. The main fund manager in Holberg Norge, Hogne Tyssøy, follows these investment "rules" when making investing decisions. These investment rules may be recognized as a behavioral strategy approach. Compared to the other selected funds listed above, Holberg Norge has not as strong behavioral characteristics but they do have stronger psychological elements compared to the remaining Norwegian fund population. The mutual fund, Holberg Norge, is therefore included in the selection of funds.

MATCHING FUNDS

To purpose of this study is also to examine the differences between conventional mutual funds and funds with a behavioral strategy. To capture the effect, one large value-fund (DnB Norge (1)), one mid-size value/growth fund (Storebrand Norge) and two index funds (PLUSS Index and Carnegie Aksje Index) are included in the dataset. These four funds are chosen due to their size, style and inception dates. By including a relative large value-fund as proxy for the conventional funds, I test that following a value-strategy does not imply following a strategy based on behavioral finance. Storebrand Norge is included since it holds a mix of value and growth strategy, and can thus be regarded as proxy for both value and growth funds. This form of comparing funds is called matching fund analysis and is common when comparing different strategies and fund performance, but could also be source of error. One cannot be totally sure that the matching and the matched fund are having the same view on the market, and the risk profile may also differ.

To further check for differences between the conventional funds and the one associated with behavioral finance, two equally weighted portfolios are created. Ew Bf contains the six behavioral mutual funds, and Ew Cf contains the remaining funds in the dataset.

5.3 OSEFX AND THE 1 MONTH NIBOR INTEREST RATE

To preform the empirical analysis, proxies for the market index and the risk-free rate are needed. This section describes the selection of benchmark and interest rate.

5.3.1 OSEFX

In order to test for abnormal performance a benchmark index is required. The chosen benchmark should reflect the funds investments in terms of both risk and composition. Using an index as benchmark makes it easy for the investor to compare the performance of the fund relative to the benchmark, and thus, see if the fund manager is able to produce abnormal returns. The index should also investable for the common investor.

Most Norwegian mutual funds use either Oslo Stock Exchange Benchmark Index (OSEBX), the sub-index Oslo Stock Exchange Mutual Fund Index (OSEFX), but the fund is free to choose any benchmark it finds suitable. However, since mutual funds are trying show abnormal performance the selection of benchmark could be somewhat biased. I their master thesis both Pedersen and Vorland (2003) and Johannessen and Johansen (2001) showed that selection of benchmark affects the abnormal performance. Their findings indicate that choosing between OSEBX and OSEFX would affect the beta-values and thus the abnormal performance. This is due to the realized market premium being different for the two indexes.

Since most of the funds in my data sample use the OSEFX as benchmark, I chose to use this index as the benchmark. The OSEFX was created 31.08.2001 to be a fair benchmark for the Norwegian mutual funds. Since my dataset contains data prior to this date, I use a linked OSEFX available on the homepage of Oslo Stock Exchange. The linked OSEFX is able to show historical information by using the total index adjusted by an adjustment ratio similar to the ratio between the total index and OSEFX at 31.08.2001.

The only fund in the sample not using OSEFX is Skagen Vekst. Skagen Vekst is using a weighted benchmark consisting and OSEBX and MSCI All Country World Index. Prior to 31.12.09, Skagen Vekst used OSEBX as benchmark. This is important to remember when analyzing the empirical results, since the wrong benchmark may affect the results. Skagen Vekst has a more international mandate, making it more possible to diversify the investments more effectively.

5.3.2 THE 1-MONTH NIBOR

In order to calculate excess return, a proxy for the risk-free rate is required. I have chosen to use the effective 1-month NIBOR (Norwegian Interbank Offered Rate), which is similar to 1-month T-bills used as risk-free rate in the Fama-French model. Using the 1-month NIBOR could be problematic due to the volatility in short time interest rates and the instability when markets are turbulent. However, the risk-free rate is always the risk-free alternative, and any short time variability is therefore irrelevant.

The data on the risk-free rate is downloaded from the homepage of Norges Bank[1], and is converted from yearly to monthly quote, using the following formula:

$$r_m = (1 + r_t^{1M})^{1/12} - 1 \tag{11}$$

[1]http://www.norges-bank.no/no/prisstabilitet/rentestatistikk/

5.4 DATA SAMPLE

The dataset is obtained from Oslo Børs and contains monthly return from 1993 to 2010. The returns are calculated using net-asset values after deducting dividends and yearly managements costs. The fund sample is selected based on the information fund managers convey to the well-known investment research firm Morningstar.

The 1-month NIBOR is subtracted from the return each month to yield excess returns, and then regressed using both the CAPM and the Carhart four-factor model. The α from the intercept, represent the abnormal performance that is not explained by the independent variables. The data sample is regressed using a standard OLS regression

Ex-post CAPM:

$$r_{pt} - r_{ft} = \alpha_{pt} + \beta_p\left(r_{mt} - r_{ft}\right) + \varepsilon_{pt} \tag{12}$$

Carhart four-factor model

$$r_{pt} = \alpha_p + b_p RMRF_t + s_p SMB_t + h_p HML_t + u_p PR1YR_t + \varepsilon_{pt} \tag{13}$$

The data related to SMB, HML and PR1YR in the Norwegian market is downloaded from the homepage of Bernt Arne Ødegaard [2]. SMB_t and HML_t are the returns on the factor portfolios created similar to Fama and French (1992) on size and book-to-market in month t. $PR1YR_t$ is the factor portfolio on the prior one-year momentum for stocks in month t. The factor portfolio RMRF is calculated using monthly return on OSEFX minus 1-month NIBOR.

TABLE 2: DESCRIPTIVE STATISTICS ON FACTOR PORTFOLIOS 1993-2010

Factor portfolio	n	Mean	Standard Deviation
RMRF	216	.0081	.073
SMB	216	.0077	.049
HML	216	.0027	.057
PR1YR	216	.0043	.049

Descriptive statistics on factor portfolios in the time period 1993-2010.

[2] http://finance.bi.no/~bernt/

To test the performance of the funds with a behavioral strategy, three standard performance measures are applied: Jensen's alpha, Sharpe Ratio and Information Ratio. The measures are calculated over the total time period and in three different sub-periods.

The total time period is 1993-2010. This long period is chosen in order to evaluate the long-term performance. In order to analyze any changes in performance, the total time period is also divided in three sub-periods. The sub-periods are 5-years intervals, and this timeframe is chosen since the Norwegian Fund and Asses Management Association recommends a holding period of at least 5 years for mutual funds.

6.0 EMPIRICAL RESULTS

Section 6.1 present the purpose of the empirical study, and section 6.2 presents the descriptive statistics for both factor portfolios and the selected funds. Section 6.3 present the empirical results examining Jensen's Alpha after carrying out a traditional regression using the CAPM. Section 6.4 presents the empirical results after carrying out regressions using the Carhart four-factor model. Section 6.5 ranks the funds in the sample according to their Sharpe's Ratio. In section 6.6 the funds are ranked using the Information Ratio and finally section 6.7 will contain a discussion and critical remarks of the empirical results.

6.1 INTRODUCTION

While mutual fund performance has been widely discussed, the practical application of behavioral finance for mutual funds is more unknown. The purpose of this empirical study is to examine whether Norwegian mutual funds associated with behavioral finance are able to deliver abnormal returns after controlling for risk, and their ability to outperform index funds. A part of the study is also to examine if the funds associated with behavioral finance load differently on the factor portfolios in the Carhart four-factor model compared to non-behavioral funds.

6.2 DESCRIPTIVE STATISTICS

Table 2, page 51, displays the descriptive statistics for factor portfolios over the time period 1993-2010. The results indicate that the market portfolio has the highest monthly returns, in line with the expectations, since the market portfolio holds the highest standard deviation. When comparing the portfolios related to size, book-to-market ratio and momentum, the statistics indicates that an investment strategy tilted towards small stocks would offer a better risk-reward for the investor than begin tilted towards value- or momentum stocks. In fact, by investing in the factor portfolio related to size, SMB, the investor would have 0.50% higher monthly returns and at the same time less risk, compared to an investment in the HML portfolio. Comparing the size and the momentum portfolios shows that the investor would have earned 0.34% more monthly returns by investing in the SMB portfolio relative to the PR1YR portfolio. These portfolios have the same standard deviation, which indicates that the SMB portfolio offered the best risk-reward ratio.

TABLE 3: DESCRIPTIVE STATISTICS ON FACTOR PORTFOLIOS 1993-1998

Factor portfolio	n	Mean	Std.
RMRF	72	.0104	.061
SMB	72	.0103	.048
HML	72	.0064	.055
PR1YR	72	.0016	.042

Descriptive statistics on the factor portfolios in the time period 1993-1998

Table 3 contains the descriptive statistics over the sub period 1993-1999. The statistics displays some similarities to the total time period. The SMB portfolio had even higher return and lower standard deviation in this time period compared to the total time period, making it an even better strategy. The portfolio related to value stocks, HML, had higher return at almost the same risk level, when comparing to the total time period. However, the return on the HML portfolio increased more relative to both the SMB portfolio and the PR1YR portfolio, indicating that value stocks outperformed both small stocks and momentum stocks. The return on the momentum portfolio was relative low in this period, only showing a monthly mean return of 0.16% while maintain almost the same level of risk. One argument for the relative strong performance of the SMB portfolio and the relative weak performance of the HML portfolio may be related to the business cycle. In the time period 1993 to 1999, the market was moving upwards as a result of the technology bubble, and interest rates were high. As presented in section 4.2, Zhang (2005) argues that value stocks underperform when the market is moving upwards.

TABLE 4: DESCRIPTIVE STATISTICS ON FACTOR PORTFOLIOS 1999-2004

Factor portfolio	n	Mean	Std.
RMRF	72	.0046	.068
SMB	72	.0070	.035
HML	72	.0084	.055
PR1YR	72	.0026	.057

Descriptive statistics on the factor portfolios in the time period 1999-2004

Table 4 displays the descriptive statistic over the time period from 1999 to 2004. This time period contains both a recession and an expansion period. It can be observed that the excess return on the market was only 0.46%, down from 0.104% in the prior time period. This is clearly a result of the high volatility in the market. On interesting result in this time period is the high return on the portfolio related to value stocks, HML. While remaining the same level of risk, the HML portfolio has passed the SMB portfolio as the best portfolio in terms of returns. However, when evaluating both risk and return, the SMB portfolio still offers the best risk to return ratio.

TABLE 5: DESCRIPTIVE STATISTICS ON FACTOR PORTFOLIOS 2005-2010

Factor portfolio	n	Mean	Std.
RMRF	72	.0092	.089
SMB	72	.0019	.060
HML	72	-.0067	.061
PR1YR	72	.0088	.046

Descriptive statistics on the factor portfolios in the time period 2005-2010

Table 5 displays the descriptive statistic over the time period from 2005 to 2010. The time period was highly volatile, due the financial crisis in 2008-2009. The volatile market explains the high standard deviation the RMRF factor. The portfolio did deliver monthly excess return of 0.92%, but at the cost of a higher than normal risk profile. Another interesting remark is the negative return on the HML portfolio. This indicates that growth stocks outperformed value stocks in this time period. Following the argument that risk is the reason why these factor portfolios deliver positive returns, the HML factor is associated with risk related financial distress. One can argue that under the financial crisis stock with high book-to-market ratio fell more than stocks with low book-to-market ratio. This supports to the argument of Fama and French (1992) and further Zhang (2006) that value stock underperform relative to growth stocks in times when the price of risk is high. In contrast to prior time periods, the factor portfolio related to momentum offered the best risk-reward ratio in this period, by having the highest return and the lowest standard deviation.

TABLE 6: DESCRIPTIVE STATISTICS ON SELECTED FUNDS

Fund	n	Mean	Std.	Min	Max
Skagen Vekst	204	0.0105	0.0549	-0.2059	0.1551
ODIN Norge	216	0.0121	0.0700	-0.2464	0.2203
Pareto Aksje Norge	111	0.0142	0.0657	-0.2664	0.1595
Delphi Norge	198	0.0110	0.0793	-0.2553	0.2250
PLUSS Aksje	168	0.0072	0.0716	-0.2611	0.1724
Holberg Norge	120	0.0093	0.0712	-0.2445	0.1570
Storebrand Norge	216	0.0084	0.0688	-0.2938	0.1652
DnBNor Norge (1)	216	0.0073	0.0652	-0.2471	0.1563
PLUSS Index	207	0.0070	0.0676	-0.2543	0.1681
Carnegie Norge Index	216	0.0073	0.0671	-0.2559	0.1671
Equally weighted portfolio. Conventional Funds	216	0.0089	0.0649	-0.2570	0.1545
Equally weighted portfolio. Behavioral Funds	216	0.0137	0.0665	-0.2409	0.2203
Oslo Stock Exchange Mutual Fund Index	216	0.0081	0.0733	-0.2882	0.2016

The table displays the descriptive statistics for all funds. Mean is calculated on excess return level and denoted as monthly excess return. The return of OSEFX is the same as the factor RMRF.

Table 6 displays the descriptive statistics for the behavioral funds, the matching funds, the market benchmark index and the two equally weighted portfolios, on an excess return basis

It can be observed that Pareto Aksje Norge has the highest mean excess return over the time period, followed by ODIN Norge and Delphi Norge. Skagen Vekst has lowest standard deviation, followed by Pareto Aksje Norge and ODIN Norge, while Delphi Norge is the fund with the highest standard deviation. The market index, OSEFX, has an average monthly excess return of 0.0081 or 9.72% annualized. The market outperformed only Pluss Aksje of the behavioral funds, but managed to outperform DnBNor Norge (1) and both index funds.

The equally weighted portfolios of behavioral funds reports both highest excess return and highest standard deviation of the two equally weighted portfolios. Both portfolios are able to outperform the market, and also have less standard deviation that the market.

6.3 Abnormal return: CAPM

In this section a regular CAPM regression is performed to test if the behavioral mutual funds are able to generate abnormal returns after controlling for risk. The test is also divided in sub-periods to examine any changes in performance.

6.3.1 Total time period

Table 7 contains the results of testing the first hypothesis using the CAPM over the total time period, 1993-2010.

Over the total time period all of the funds have positive alpha values, and thereby higher excess returns than predicted by the CAPM. Two of the funds have significant alpha-values on a 5% significance level, Odin Norge (ODN), and Pareto Aksje Norge (PAA), while Skagen Vekst (SKV) has a significant alpha-value on 1% significance level.

The index funds PLUSS Index (PI) and Carnegie Norge Index (CNI) have respectively 1.38% and 0.39% annualizes alpha-values, but none of them are statistical significant. Since both of the index funds are designed to follow the movement on OSEBX the positive alpha could be a result of a difference between OSEFX and OSEBX. However, alpha-values that are not statistical significant are in line with expectations of the model.

As for the beta-values, the model produces significant values at a 1% significant level for all funds. The beta-values range from 0.635 (SKV) to 0.895 (DNH). The beta-values are relative low for index fund, and similar to the alpha-value, the low beta-values could be a result of the difference between OSEBX and OSEFX.

The relative low R^2 for ODN and PAA could be an indication that these funds are not diversified enough, and holds more unsystematic risk than necessary. However, being a behavioral mutual fund might involve taking on extra risk in order to exploit mispricing in the market, but one would expect large funds to be diversified enough to fully utilize the diversification effect. Since PI is an index fund, one would expect the fund to have a higher R^2 than 0.87. The low R^2 could be due to the low number of observations or the high volatility in the market for the selected time-period.

The two equally weighted portfolios are also regressed over the period, and interesting the Ew Bf has a significant monthly excess return of 0.007. This is in contrast to most of the prior studied on fund performance, as described in section 4.0. The equally weighted portfolio of conventional funds, Ew Cf, a positive alpha, but this value is not significant.

In contrast to prior studies (Gjerde & Sættem, 1991; Sørensen, 2009) the results indicates that my first hypothesis might be rejected.

Comparing the results to other master thesis reveals some similarities. Daphu (2007) analyzed the time period from 1999 to 2006, and found that Skagen Vekst (0.0075) and Pareto Aksje Norge (0.0100) were able to deliver significant alpha. Myrmel (2008) used the time period from 1999 to 2005 and also found Skagen Vekst (0.0089) being able to deliver significant alpha at 1% level. Tveito (2006) analyzed the period from 1998-2005, and found that Holberg Norge was able to deliver significant alpha at 5% significant level, while Pareto Aksje Norge was able to deliver significant alpha at 1% significant level.

Since three out of six funds deliver associated with behavioral finance are able to deliver significant abnormal returns, this could be an indication that behavioral finance is somewhat useful in portfolio management. However, it is important to remember that CAPM only captures the systematic risk related to the market, and further analysis might give different results when adding more risk-sources.

TABLE 7: ABNORMAL RETURNS: CAPM 1993-2010

		1993-2010			
Ticker	α	Annualized-α	β	R^2	n
SKV	0.006**	7.72 %	0.635**	0.73	204
	(3.22)		(28.56)		
ODN	0.006*	6.87 %	0.788**	0.68	216
	(2.11)		(21.31)		
PAA	0.008*	9.00 %	0.659**	0.70	111
	(2.17)		(15.91)		
DHN	0.005	5.82 %	0.894**	0.71	198
	(1.58)		(21.78)		
PLA	0.002	2.81 %	0.827**	0.84	168
	(1.04)		(29.13)		
HBN	0.004	5.39 %	0.761**	0.79	120
	(1.49)		(21.00)		
PI	0.001	1.37 %	0.850**	0.87	207
	(0.66)		(36.46)		
CNI	0.000	0.39 %	0.855**	0.87	216
	(0.20)		(38.04)		
Eq Cf	0.002	2.60 %	0.825**	0.87	216
	(1.34)		(37.42)		
Eq Bf	0.007**	8.75 %	0.793**	0.76	216
	(3.28)		(26.23)		

**SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL

The estimated alpha- and beta-values are the regression coefficient from the CAPM. The dependent variable is portfolio return above the risk-free rate for all funds. T-values are indicated in the line below the regression estimates (grey line). The t-value are tested against α=0 and β=0

6.3.2 Sub periods

In this section the results of the different sub periods is presented, in order to give a more in-depth understanding of the funds performance.

Table 8 contains the CAPM regression over the time period 1993-1998. Since behavioral finance is a rather new discipline, one could expect the funds to have had a different strategy in this period time-period than today, and thus obtain different results.

Only Skagen Vekst (SKV) has significant alpha in this period, but all of the behavioral funds performed better than estimated by the CAPM model. The two index fund has negative alpha in this period, but none of the results are statistical significant.

The beta-values in this period are highly volatile and SKV has a beta-value of only 0.52. This could be due to the fact that SKV was incepted 01.1994, and has only 60 month of trading activity in this period. ODN has an estimated beta-value of 0.93 in this time period, in contrast to the beta-value of 0.788 for the whole period, 1993-2010. The R^2 for ODN is about the same in this period, as for the whole period, which could indicates that the fund simply follows the index to a larger extend or is more diversified, lowering the unsystematic risk.

The equally weighted portfolio of behavioral funds performed extremely well in this period, earning an annualized alpha of 13.06%, but the portfolio has a low R^2 , and could hold a lot of unsystematic risk. Compared to the equally weighted portfolio of conventional funds, the behavioral portfolio earned over 10% annualized alpha more than the conventional portfolio in this time period.

The results in this period make it difficult to give a clear conclusion regarding the hypothesis of behavioral fund delivering abnormal returns. While three out of four funds does not deliver significant abnormal returns, the equally weighted portfolio does. I would argue that due to the low number observations for two of the funds in the sample, the result regarding the equally weighted portfolio of behavioral funds must be used with caution.

Table 9 displays the result from the CAPM regression over time period 1999 to 2004.

In this period all of the funds in the sample have positive alpha values and three, Skagen Vekst, Odin Norge and Pareto Aksje Norge, of the behavioral funds have a significant alpha value. All of the behavioral funds seem to have performed exceptionally good in this time period, especially when comparing to equally weighted portfolio of conventional funds. The behavioral funds also outperformed the index funds PI and CNI, as expected, in the matter of alpha. The beta-values are in this time-period generally higher than in the prior time period. This could be seen as an adjustment of the risk towards systematic risk, rather than unsystematic risk. The high beta-values also correspond to the higher R^2 .

The time period 01.1999 to 12.2004 was a highly volatile period containing both an expansion and a recession period. After the IT-bubble and the terrorist attack in September 2001 the economy fell into recession, and the stock market fell deeply and was over halved during the period from 09.2000 to 03.2003. Following the recession, the market quickly recovered and expands heavily from 04.2003 and to the end of this time period. During this expansion the market recovered all of the loss from the recession and expanded even further. This might explain some of the great returns.

Table 10 contains the estimated beta and alpha values from the CAPM in the time period 2005-2010.

In this time period all funds in the sample have positive alpha values, but none of the values holds as statistical significant. Pareto Aksje Norge and Holberg Norge are to the two best-performing funds delivering annualized alpha of 7.47% and 6.65%, while Odin Norge is the worst performing fund, delivering only 2.41 % annualized alpha. Also in this period the index funds perform better than estimated by CAPM, but the result are, as expected, not statistical significant.

The beta values have changed quite much compared to earlier sub-periods and the total time period, and all funds have smaller beta values compared to 1994-2004. This could be an indication that funds reduce their exposure to the volatility in the market in volatile times. The low beta value can also be a result of the funds holding more of their capital in cash or investing in the risk-free alternative.

The R^2 is fairly similar in this period to the overall period of 1993-2010, but both HBN and ODN have relative small R^2 meaning they are less diversified.

In the discussion regarding behavioral finance and convection funds, Ew Bf again seems to outperform the Ew Cf, but none of the alpha values are found to be statistical significant different from zero, and thus the null hypothesis testing α=0 fails to be rejected.

TABLE 8: ABNORMAL RETURNS: CAPM: 1993-1998

		1993-1998			
Ticker	α	Annualized-α	β	R^2	n
SKV	0.008*	9.26 %	0.521**	0.59	60
	(2.24)		(9.31)		
ODN	0.006	6.78 %	0.939**	0.68	72
	(1.20)		(12.28)		
DHN	0.006	6.83 %	0.835**	0.62	54
	(1.02)		(9.36)		
PLA	0.005	5.83 %	0.924**	0.73	24
	(0.61)		(8.02)		
PI	-0.001	-1.72 %	0.962**	0.90	63
	(-0.57)		(23.67)		
CNI	-0.003	-3.17 %	0.952**	0.90	72
	(-1.17)		(25.94)		
Eq Cf	0.002	2.57 %	0.823**	0.86	72
	(0.88)		(20.78)		
Eq Bf	0.011*	13.06 %	0.871**	0.66	72
	(2.42)		(11.89)		

**SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL

The estimated alpha- and beta-values are the regression coefficient from the CAPM. The dependent variable is portfolio return above the risk-free rate for all funds. T-values are indicated in the line below the regression estimates (grey line). The t-value are tested against a=0 and b=0.

TABLE 9: ABNORMAL RETURNS CAPM: 1999-2004

		1999-2004			
Ticker	α	Annualized-α	β	R^2	n
SKV	0.008*	10.03 %	0.808**	0.80	72
	(2.60)		(16.95)		
ODN	0.009*	10.47 %	0.969**	0.78	72
	(2.12)		(15.81)		
PAA	0.009*	10.95 %	0.716**	0.77	72
	(1.97)		(11.20)		
DHN	0.005	5.66 %	1.183**	0.76	72
	(0.90)		(15.10)		
PLA	0.001	1,04 %	0,9443**	0,88	72
	(0.310)		(22.74)		
HBN	0.004	4,57 %	0.963**	0.89	48
	(1,040)		(19,31)		
PI	0.002	2.60 %	0.888**	0.92	72
	(1.04)		(28.54)		
CNI	0.001	1.30 %	0.899**	0.93	72
	(0.53)		(29.80)		
Eq Cf	0.001	1.72 %	0.947**	0.92	72
	(0.63)		(27.83)		
Eq Bf	0.006*	7.65 %	0.950**	0.88	72
	(2.25)		(22.54)		

****SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL**

The estimated alpha- and beta-values are the regression coefficient from the CAPM. The dependent variable is portfolio return above the OSEFX for all funds. T-values are indicated in the line below the regression estimates (grey line). The t-value are tested against a=0 and b=0.

TABLE 10: ABNORMAL RETURNS: CAPM: 2005-2010

		2005-2010			
Ticker	α	Annualized-α	β	R^2	n
SKV	0.004	4.35 %	0.5821*	0.773	72
	(1.090)		(15.570)		
ODN	0.0020	2.41 %	0.6137*	0.661	72
	(0.430)		(11.820)		
PAA	0.0064	7.74 %	0.6387*	0.669	72
	(1.360)		(12.010)		
DHN	0.0046	5.58 %	0.7507*	0.762	72
	(1.050)		(15.120)		
PLA	0.0033	3.98 %	0.7316*	0.873	72
	(1.130)		(22.130)		
HBN	0.0055	6.65 %	0.6693*	0.749	72
	(1.360)		(14.600)		
PI	0.0011	1.37 %	0.8500*	0.866	72
	(0.660)		(36.460)		
CNI	0.0020	2.38 %	0.7846*	0.824	72
	(0.520)		(18.260)		
Eq Cf	0.0030	3.64 %	0.7550*	0.847	72
	(0.900)		(19.860)		
Eq Bf	0.0043	5.12 %	0.6644*	0.792	72
	(1.190)		(16.480)		

****SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL**

The estimated alpha- and beta-values are the regression coefficient from the CAPM. The dependent variable is portfolio return above the OSEFX for all funds. T-values are indicated in the line below the regression estimates. The t-value are tested against a=0 and b=0.

6.4 ABNORMAL RETURNS: CARHART FOUR-FACTOR MODEL

In this section the results of testing the funds for abnormal performance using the Carhart four factor is presented. The testing is conducted over the total time period, as well as sub periods in order to evaluate the hypotheses formed in the introduction .

6.4.1 TOTAL TIME PERIOD

Table 11 contains the results of estimating Carhart (1997) four-factor model for risk over the total sample period ranging from January 1993 to December 2010. The parameter estimates and corresponding t-values and p-values are regressed using the following equation:

$$r_{pt} = \alpha_p + b_p RMRF_t + s_p SMB_t + h_p HML_t + u_p PR1YR_t + \varepsilon_{pt} \quad (14)$$

The estimated intercept, which represent abnormal return, is positive for all funds, but only statistical significant for Skagen Vekst (0.005). However, Skagen Vekst is the only fund having a different benchmark and the fund has a boarder investment mandate, which could indicate that the realization abroad has contributed to the good performance of the fund. Since only one of the behavioral funds show significant alpha-value, this indicates that on an aggregate level, it is possible to conclude that the testing fails to reject the null hypothesis of H1, that behavioral mutual funds earn zero abnormal returns. The equally weighted portfolio also supports this conclusion, not having a statistical significant alpha value. These findings are in line with the results from earlier testing, both on behavioral mutual fund and on conventional mutual fund both under CAPM and the Carhart model (Burton, 1995; Gjerde & Sættem, 1991; Sørensen, 2009; Wermers, 2000; Wright, et al., 2006). Using the Carhart model on an equally weighted portfolio for the time period 1986 to 2009, Sørensen (2009) reports a monthly alpha of 0.002, which is quite similar to my result on the equally weighted portfolio of conventional funds delivering monthly alpha of 0.001. The equally weighted portfolio consisting of the behavioral funds deliver slightly higher alpha, 0.004, but none of the values are found to be statistical significant.

The market coefficient varies from 0.693 (Skagen Vekst) to 0.987 (Delphi Norge). Only two of six behavioral mutual funds have higher market coefficient than the matching funds, which could indicates that the behavioral mutual funds invest more freely regarding the market index. Since the results display that behavioral funds, on an aggregate level, have a higher beta coefficient than the conventional funds, it is difficult to draw any strong conclusions regarding the differences. Another interesting observation is the relative low coefficient of the index funds, respectively 0.847 (Pluss Index) and 0.847 (Carnegie Norge Index). This could be a result of the index funds tracking the OSEBX while they are tested against the OSEFX.

The coefficient for SMB factor has high variability, both for the behavioral mutual funds and the matching funds. It ranges from -0.054 (CNI) to 0.378 (ODN). A positive coefficient on the SMB factor indicates going long small stocks and short large stocks. Five out of six behavioral mutual funds have statistical significant factor loading on the SMB factor, compared to only one of the matched and index funds.

On the HML factor almost all of the funds have positive coefficients, but only the coefficients of ODN and PAA holds as significant at 5% level. The significant values of PAA and ODN are in line with the expectation since both funds use value investing as a part in their investments strategy. Having a positive (negative) coefficient indicates going long (short) stocks with low (high) book-to-market ratio. DHN is the only fund having a negative coefficient. The results at the HML factor can be compared, at an aggregated level, to the findings of Sørensen (2008). While he reports a negative factor loading on the HML factor, my result shows a significant positive value, and this could be an indication that there is a difference between behavioral and non-behavioral funds. My results are similar to the finding of Wright et al. (2006), which also reports a significant coefficient on the HML factor.

On the momentum none of the funds have significant coefficients. This indicates that none of the funds systematically use momentum as a part of their strategy. However, the results shows that four out of six behavioral find have negative coefficient on the momentum factor, indicating going long prior losers and short prior winners. This is in line with reversal effect discovered by De Bondt and Thaler (1985). The result also indicates that Delphi Norge, which has defined momentum as part of their investments strategy, does not seem to statistically follow this strategy. However, this could be a result of the long time period, whereas Delphi uses more short-term momentum.

The results displays that the systematic risk, R^2, range from 0.70 to 0.90. Compared to the result of Wright et al. (2006), R^2 seems to be about the same, but with a lower maximum value. At the aggregate level, my results also seem to have a lower R^2 than the result from Sørensen (2009) both on the equally weighted portfolio of conventional and on the equally weighted portfolio of behavioral funds. This could a result of the selection of risk-free rate or the selected time period. Also compared to Reizer (2010) and Hoel (2010), my results show a lower R^2, but this could be a result of different benchmarks or the time periods selected.

In short summary of my results, I view my results providing support to earlier studies. The empirical results indicate that behavioral funds are not able to deliver abnormal returns after controlling for risk, hence, H1 fails to be rejected.

The results further indicate that funds associated with behavioral finance, load differently than conventional funds on the HML factor in the Carhart (1997) model. Two of the behavioral funds have significant coefficients on the HML factor, which could be an indication that my second hypothesis is fails to be rejected, and that behavioral and non-behavioral funds load differently on the Carhart factors. I will also argue that the equally weighted portfolio has a significant factor loading on the HML factor, a further indication that behavioral mutual funds are more into value investing. Wright et al. (2006) also find significant coefficient on the HML factor, both with an equally weighed and a value-weighted portfolio. Their result then supports my finding that behavioral funds are indeed more into value investing than conventional funds. However, as mention earlier, it is important to remember the small sample and both the rational and the behavioral explanation for value investing.

The lack of prior studies using the Carhart model in the Norwegian market makes it difficult to compare the results for the factor loadings. At the aggregate level my results displays a significant positive factor loading on the SMB factor both on the portfolio of conventional and behavioral funds, in contrast to Sørensen (2009) and Wright et al. (2006) who reports insignificant factor loading on SMB.

TABLE 11: ABNORMAL RETURNS: CARHART FOUR-FACTOR MODEL: 1993-2010

Ticker	α	β	s	h	u	Adj. R^2	n
SKV	0.005**	0.693**	0.197*	0.046	-0.052	0.74	204
	(2.67)	(20.67)	3.46	(1.08)	(-1.24)		
ODN	0.002	0.903**	0.378*	0.220**	-0.067	0.74	216
	(0.61)	(22.76)	(6.27)	(4.75)	(-1.29)		
PAA	0.006	0.743**	0.165*	0.164*	0.067	0.70	111
	(1.70)	(13.12)	(1.73)	(2.15)	(0.97)		
DHN	0.002	0.987**	0.306*	-0.084	0.041	0.74	198
	(0.79)	(19.6)	(3.57)	(-1.29)	(0.67)		
PLA	0.002	0.855**	0.102	0.014	-0.035	0.84	168
	(0.88)	(22.74)	(1.61)	(0.29)	(-0.76)		
HBN	0.004	0.829**	0.202*	0.082	-0.047	0.79	120
	(1.25)	(16.63)	(2.35)	(1.26)	(-0.76)		
STBN	0.000	0.909**	0.097*	0.033	-0.007	0.88	216
	(0.16)	(34.01)	(2.38)	(1.07)	(-0.19)		
DNBN	0.000	0.846**	0.026	0.010	0.016	0.88	216
	(0.09)	(33.70)	(0.69)	(0.36)	(0.49)		
PI	0.001	0.847**	-0.030	0.027	0.028	0.87	207
	(0.63)	(28.55)	(-0.599	(0.72)	(0.75)		
CNI	0.001	0.845**	-0.054	0.017	0.035	0.87	216
	(0.36)	(31.88)	(-1.33)	(0.57)	(1.02)		
Ew Cf	0.001	0.865**	0.122*	0.004	0.021	0.87	216
	(0.48)	(33.81)	(3.13)	(0.14)	(0.64)		
Ew Bf	0.004	0.894**	0.338*	0.131**	-0.049	0.80	216
	(1.77)	(27.63)	(6.86)	(3.47)	(-1.16)		

**SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL

Table 11 contains the parameter estimates and the corresponding t-values from estimating the Carhart model on each fund. The estimated intercept represents the risk-adjusted abnormal performance. s, h and u are the regression coefficient of the three factor portfolios, SMB, HML and PR1YR, while β, is the regression coefficient regarding RMRF

6.4.2 SUB PERIODS

To further analyze the regression over the Carhart four-factor model, it is interesting to see if any of the factor loading change heavily during different time period. Testing the funds in different time periods could also be regarded as test for persistence and robustness.

Table 12 contains the regression results of estimating Carhart (1997) four-factor model over the sample period ranging from 1993 to 1998.

In this time period only SKV and PLA of the behavioral funds have positive intercepts, while all of the other funds have negative intercept. The best performing fund was SKV with a monthly alpha of 0.004, while ODN and PLA were the worst performing funds delivering monthly alpha of -0.003. However, none of the intercepts are significant and thus adds further support to the final conclusion, failing to reject the null hypothesis. Three (SKV, ODN and DHN) out of the four behavioral funds deliver less alpha in this time period compared to the total time period, and also the equally weighted portfolio of behavioral funds, Ew Bf, delivers less alpha.

Three of the funds (ODN, DHN and PLA) have market coefficients higher than 1, meaning they are more exposed to the volatility in the market. The result is similar to the results of Wright et al. (2006), which found the behavioral funds having universally high loadings on the market coefficient, approximately of 1. Compared to the total time period, three funds have an increase in the market coefficient, while the last fund, SKV, has a decrees. This could indicate that the funds were willing to take on more risk to capture the great development in the market. At the aggregate level, both equally weighted portfolios have an increased market coefficient. The increase is more prominent for the portfolio of behavioral funds, having a market coefficient of 0.966 in this time period, compared to 0.894 for the total time period.

The SMB coefficients in this period are generally higher compared to the total time period. Three (SKV, ODN and PLA) out of the four behavioral funds have higher coefficients, and also the both equally weighted portfolios have increased their loading on the SMB factor. Having a higher coefficient on the SMB factor indicates that the funds are more into stocks with low market capitalization in this time period.

For the HML factor, three funds (ODN, DHN and PLA) have reduced their coefficient compared to the total time period, meaning they are less into stock with high book-to-market ratio. Three of the funds have still significant values on the HML factor, leading to the equally weighted portfolio also having significant value. At the aggregate level, the absolute value of the coefficient is even higher in this period, compared to the total time period, supporting the decision of behavioral fund in the sample are value-oriented. The portfolio of conventional funds has an insignificant value, which adds further support to the result that conventional and behavioral fund do load differently on the HML factor.

For the momentum factor PR1YR, two funds (SKV and DHN) have increased coefficient compared to the total time period, meaning they are more into stock with good prior performance. However, only ODIN Norge has a significant coefficient on the momentum factor. At the aggregate level, also the portfolio of conventional funds has a significant value. This indicates that conventional funds used the momentum strategy in this period.

Table 13 contains the regression results of estimating Carhart (1997) four-factor model over the sample period ranging from 1999 to 2004.

In this time period all funds have positive alpha-values, but only the result of Skagen Vekst (0.009) holds as statistical significant. The alpha values are higher or fairly similar in this period, compared to the prior period and the total period, and the coefficient ranges from 0.009 (SKV) to 0.000 (STBN). The equally weighted portfolio of behavioral funds, also delivers significant alpha, in contrast to prior studies and my main conclusion. The results in this period also add support to the conclusion that behavioral funds are able to outperform index funds and non-behavioral funds.

Comparing this period to prior periods reveals only small differences in terms of factor loadings. The period contains only a few significant values that are worth commenting: None of the funds hold significant values on the SMB factor, indicating that none of the funds used the size-premium in this period. Further, on the HML only PAA and DHN holds positive significant coefficients, in line with the expectations considering the funds profile about value investing. In contrast, the equally weighted portfolio of conventional funds holds a significant negative coefficient, similar the findings of Sørensen (2009). On the momentum factor PR1YR, only PLA has a significant coefficient and, in line with the expectations about reversal found by De Bondt et al. (1985), the coefficient is negative.

The R^2 is higher for all funds in this period when comparing to the total period, indicating the funds being more diversified.

Table 14 contains the regression results of estimating Carhart (1997) four-factor model over the sample period ranging from 2005 to 2010.

In this time period all funds have positive intercepts for alpha, but none holds as statistical significant. This could be a result of the highly volatile market in this period. This notion is further backed by the decrease of the adjusted R^2. Four of the behavioral funds have lower R^2 in this time period, and all of the funds in the sample have seen a decrease in R^2. A low R^2 is an indication of low diversification in the funds, which indicates that the funds have taken on more unsystematic risk in this period. This must also be seen against the market coefficients. All funds recued their market coefficient from the prior time period, and also have lover market coefficient than for the total time period. This may indicate that the funds reduced their overall diversification because of the volatility in the market or held more of their funds in cash or bonds, as suggested by Gjerde and Sættem (1991)

Comparing this period to the prior period reveals only small differences in terms of factor loadings. However, the only significant value is the SMB coefficient for ODN, which could indicate the funds being more tilted toward a general index strategy, since none of them are statistically significantly using the factor portfolios.

TABLE 12: ABNORMAL RETURNS: CARHART FOUR-FACTOR MODEL: 1993-1998

Ticker	α	β	s	h	u	Adj. R^2	n
SKV	0.004	0.585**	0.234*	0.250**	0.189	0.67	60
	(1.28)	(9.66)	(2.21)	(3.00)	(1.95)		
ODN	-0.003	1.002**	0.452**	0.210**	-0.191*	0.81	72
	(-0,650)	(15.44)	(5.63)	(3.02)	(-2.15)		
DHN	-0.003	1.020**	-0.130	0.496**	0.306*	0.77	54
	(-0.64)	(11.74)	(-1.03)	(3.20)	(2.28)		
PLA	0.004	1.145**	0.617**	-0.221	-0.174	0.81	24
	(0.47)	(8.65)	(2.60)	(-1.02)	(-0.75)		
STBN	-0.001	0.910**	0.152	0.076	0.041	0.85	72
	(-0.38)	(18.69)	(2.52)	(1.46)	(0.62)		
DNBN	-0.003	0.856**	0.061	0.037	0.043	0.90	72
	(-1.14)	(23.20)	(1.34)	(0.94)	(0.85)		
PI	-0.002	0.947**	0.007	0.112	0.043	0.90	63
	(-0.62)	(19.34)	(0.97)	(0.062)	(0.541)		
CNI	0.001	0.845**	-0.054	0.017	0.035	0.87	72
	(0.36)	(31.88)	(-1.33)	(0.57)	(1.02)		
Ew Cf	-0.002	0.874**	0.190**	0.048	0.116*	0.88	72
	(-0.67)	(21.92)	(3.86)	(1.14)	(2.31)		
Ew Bf	0.002	0.966**	0.498**	0.170*	-0.061	0.80	72
	(0.47)	(15.46)	(6.45)	(2.54)	(-0.71)		

**SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL

Table 12 contains the parameter estimates and the corresponding t-values from estimating the Carhart model on each fund in the time period 1993-1998. The estimated intercept α represents the risk-adjusted abnormal performance. s, h and u are the regression coefficient of the three factor portfolios, SMB, HML and PR1YR, while β, is the regression coefficient regarding RMRF. . T-values are indicated in the line below the regression estimates, and are tested against α=0, β=0, s=0 h=0, u=0.

TABLE 13: ABNORMAL RETURNS: CARHART FOUR-FACTOR MODEL: 1999-2004

Ticker	α	β	s	h	u	Adj. R^2	n
SKV	0.009*	0.784**	0.076	-0.073	-0.057	0.80	72
	(2.50)	(12.87)	(0.67)	(-1.01)	(-0.93)		
ODN	0.006	1.039**	0.115	0.147	0.030	0.78	72
	(1.40)	(13.18)	(0.78)	(1.58)	(0.38)		
PAA	0.005	0.787**	0.041	0.267*	0.086	0.80	39
	(0.96)	(8.98)	(0.24)	(2.09)	(0.97)		
DHN	0.006	1.134**	0.276	-0.296*	-0.058	0.81	72
	(1.11)	(12.64)	(1.64)	(-2.79)	(-0.65)		
PLA	0.002	0.898**	-0.029	-0.011	-0.117*	0.88	72
	(0.56)	(17.09)	(-0.30)	(-0.17)	(-2.23)		
HBN	0.004	0.964**	0.118	-0.052	-0.048	0.89	48
	(1.12)	(13.12)	(0.76)	(-0.55)	(-0.60)		
STBN	0.000	0.941**	-0.065	-0.067	-0.037	0.94	72
	(0.21)	(24.27)	(-0.90)	(-1.46)	(-0.95)		
DNBN	0.001	0.913**	-0.100	-0.051	-0.029	0.94	72
	(0.73)	(25.93)	(-1.52)	(-1.22)	(-0.83)		
PI	0.003	0.851**	-0.118	-0.031	-0.023	0.92	72
	(1.53)	(21.30)	(-1.59)	(-0.65)	(-0.56)		
CNI	0.003	0.858**	-0.136	-0.033	-0.021	0.93	72
	(1.17)	(22.34)	(-1.9)	(-0.74)	(-0.55)		
Ew Cf	0.002	0.914**	0.022	-0.122*	-0.012	0.92	72
	(1.04)	(21.85)	(0.28)	(-2.46)	(-0.29)		
Ew Bf	0.006*	0.941**	0.083	-0.066	-0.019	0.88	72
	(2.10)	(17.47)	(0.93)	(-1.04)	(-0.36)		

**SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL

Table 13 contains the parameter estimates and the corresponding t-values from estimating the Carhart model on each fund in the time period 1999-2004. The estimated intercept α represents the risk-adjusted abnormal performance. s, h and u are the regression coefficient of the three factor portfolios, SMB, HML and PR1YR, while β, is the regression coefficient regarding RMRF. . T-values are indicated in the line below the regression estimates, and are tested against α=0, β=0, s=0 h=0, u=0.

TABLE 14: ABNORMAL RETURNS: CARHART FOUR-FACTOR MODEL: 2005-2010

Ticker	α	β	s	h	u	Adj. R^2	n
SKV	0.004	0.642**	0.150	0.079	-0.027	0.77	72
	(1.04)	(12.38)	(1.76)	(1.13)	(-0.36)		
ODN	0.001	0.73**	0.272*	0.153	0.014	0.67	72
	(0.38)	(10.31)	(2.35)	(1.61)	(0.14)		
PAA	0.006	0.717**	0.169	0.130	0.039	0.67	72
	(1.22)	(9.67)	(1.39)	(1.30)	(0.37)		
DHN	0.003	0.851**	0.190	0.131	0.168	0.77	72
	(1.76)	(12.67)	(1.73)	(1.45)	(1.76)		
PLA	0.003	0.754**	0.024	0.063	0.075	0.87	72
	(0.93)	(16.34)	(0.32)	(1.01)	(1.14)		
HBN	0.005	0.763**	0.198	0.15	0.069	0.76	72
	(1.14)	(12.16)	(1.93)	(1.77)	(0.77)		
STBN	0.002	0.861**	0.084	0.075	0.072	0.88	72
	(0.61)	(15.49)	(0.92)	(1.00)	(0.91)		
DNBN	0.002	0.785**	0.013	0.043	0.133	0.83	72
	(0.45)	(14.0)	(0.14)	(0.57)	(1.67)		
PI	0.001	0.767**	-0.067	-0.013	0.113	0.82	72
	(0.34)	(12.74)	(-0.68)	(-0.16)	(1.32)		
CNI	0.001	0.771**	-0.069	-0.010	0.127	0.82	72
	(0.27)	(12.9)	(-0.71)	(-0.12)	(1.49)		
Ew Cf	0.002	0.800**	0.081	0.068	0.080	0.85	72
	(0.64)	(15.07)	(0.93)	(0.95)	(1.06)		
Ew Bf	0.004	0.743**	0.167	0.118	0.056	0.88	72
	(0.96)	(13.40)	(1.84)	(1.58)	(0.72)		

****SIGNIFICANT ON 1% LEVEL, * SIGNIFICANT ON 5% LEVEL**

Table 14 contains the parameter estimates and the corresponding t-values from estimating the Carhart model on each fund in the time period 2005-2010. The estimated intercept α represents the risk-adjusted abnormal performance. s, h and u are the regression coefficient of the three factor portfolios, SMB, HML and PR1YR, while β, is the regression coefficient regarding RMRF. . T-values are indicated in the line below the regression estimates, and are tested against α=0, β=0, s=0 h=0, u=0.

6.4.3 SUMMARY OF THE SUB PERIODS

The result from the regressions over the different sub periods are interesting: Firstly, some of the funds seems to be consistent in term of factor loading, and have only small variations over the different time periods, while other shift factor loading quite remarkably. PAA seems to have a consistent strategy, and has only small variation regarding the factor loadings, while PLA and DHN deviate more. From the period 1999-2004 to the period 2005-2010 PLA shift their factor loading from negative to positive regarding the SMB, HML and the PR1YR portfolios. Using the rational approach to combine SMB, HML and PR1YR with their respective risk, changes in factor loading may be regarded as changes in risk. Huang et al. (2010) argues that risk shifting could be a result of agency issues or the activeness of the fund manager. The general conclusion is that risk shifting is harmful for the investor and should be avoided. However, since both the equally weighted portfolios also seems to be subject to changes of factor loading, I would argue that risk shifting is quite common under active portfolio management. Risk shifting could also be argument for superior skills of the fund manager, since the manager is using the skills to change stock selections or utilizing timing abilities (J. C. Huang, et al., 2010).

Secondly, the results of the different sub-periods add support to the conclusion that behavioral funds load differently than conventional funds on of the factor portfolios. This can be observed from the results on the two equally weighted portfolios, and the differences between the behavioral funds and the matching funds.

6.5 SHARPE RATIO

Table 15 contains the calculations of the Sharpe Ratio for the total time period and for all sub-periods.

By ranking the funds according to Sharpe Ratio, the investor is able to analyze fund performance in terms of total risk. A fund can have higher returns than other funds, but is only a good investment if the higher returns are not a result of higher risk.

Over the total period five out of the six behavioral funds are able to outperform both the market and the two matching funds. It can be observed that Pareto Aksje Norge (PAA) has the highest Sharpe Ratio, 0.2054, followed by Skagen Vekst (SKV) (0.1907) and ODIN Norge (ODN) (0.1738). The worst performing fund is PLUSS Aksje (PLA) with a Sharpe Ratio 0.098 and the fund is thereby outperformed by both the index funds and the market index. The market index is ranked as number ten, and has a Sharpe Ratio of 0.1112

Examining the sub-periods reveals variation in the ranking, and thus only slightly persistence in the performance. ODN being the second best fund in the two first periods ranks only as number eight in the last time period, but still managed to outperform the market. Since the sub periods are five-years intervals, the investor should not use prior performance as an indicator for future performance, due to the variations in the raking.

The equally weighted portfolios of conventional funds, Ew Cf, and the equally weighted portfolio of behavioral finds, Ew Bf, rank six and first and both portfolios outperform the market, the matching funds and the index funds. This is in line with the expectations, and adds further support to the conclusion that behavioral funds are able to outperform index funds.

Since the majority of studies in the Norwegian market concerns non-behavioral funds, the results of this study could be compared to other studies in order to examine any differences between behavioral and non-behavioral funds: Tveito (2006) found that three out of 14 found were able to outperform the market index. Daphu (2007) found three out of nine funds being able to outperform the market index, and Myrmel (2008) found 15 out of 27 funds being able to beat the market index. Compared to theses studies, my results indicate that behavioral funds are, in a greater extent, able to outperform the market index.

TABLE 15: SHARPE'S RATIO

Ticker	1993-1998	Rank	1999-2004	Rank	2005-2010	Rank	1993-2010	Rank
OSEFX	0.1707	6	0.0686	11	0.1050	13	0.1112	10
SKV	0.2449	2	0.1994	2	0.1552	4	0.1907	3
ODN	0.2220	3	0.1790	3	0.1163	12	0.1738	4
PAA	N/A		0.2857	1	0.1803	1	0.2054	1
DHN	0.1663	7	0.1116	5	0.1534	5	0.1376	5
PLA	0.0464	11	0.0770	9	0.1464	6	0.0984	13
HBN	N/A		0.0706	10	0.1728	2	0.1235	7
STBN	0.1894	5	0.0542	13	0.1353	8	0.1234	8
DNBN	0.1401	8	0.0678	12	0.1338	9	0.1127	9
PI	0.0764	10	0.1006	6	0.1241	10	0.1026	12
CNI	0.1194	9	0.0832	8	0.1216	11	0.1088	11
Ew Cf	0.1981	4	0.0872	7	0.1389	7	0.1373	6
Ew Bf	0.3062	1	0.1577	4	0.1588	3	0.2071	2

Table 15 displays the results from calculating Sharpe Ratio for all funds over the different time periods.

6.6 INFORMATION RATIO

Table 16 and 17 contains the calculations of Information ratio for all time periods using CAPM and the Carhart four-factor model.

As presented in section 2.6.4 Information Ratio is used to test the fund managers' ability to create excess return above the benchmark, and can also be used to test persistence in performance. The application of information ratio in this study is to test how the behavioral funds perform relative to index funds, matching funds and further compare the equally weighted portfolios.

Table 13 displays the results of the calculations using the CAPM. Over total time-period all of the funds have positive IR. Best ranked are Skagen Vekst and Pareto Aksje with respectively information ratio of 0.2213 and 0.2077. All of the behavioral funds rank higher than the matching funds (STBN and DNBN), the index funds (PI and CNI). This is in line with the finds of Reinhart and Brennan (2007) and Wright et al. (2006)

The equally weighted portfolio consisting of behavioral funds has the highest rank in two out of three periods, and thus ranks as number one over the total time period. This could be a result of the low tracking error. The equally weighted portfolio of conventional funds is ranked as number seven, outperforming PLA, the matching fund and the index funds.

Even though the behavioral funds are ranked higher than the matching funds, index funds and the equally weighted portfolio of conventional funds, there seems to be more variability in their performance. Both SKV and ODN are ranked high, second and third, in the two first periods, but are ranked 11 and 12 in the last period. This could be an indication of funds performing better than the benchmark in economical stabile times, relative to time periods with high volatility. However, it is worth mentioning that some funds with good prior performance are able to outperform the market also in turbulent times, like PAA and DHN.

The findings are in line with prior studies. Both Tveito (2006) and Grønsund and Lunde (2010) find both negative and positive information ratios, but slightly more on the positive side.

Table 14 displays the results of calculating the Information ratio using the Carhart four-factor model. Comparing the results using Carhart and CAPM display some differences: The absolute values of information ratio are lower, indicating that the Carhart model captures more of the variability in stock prices, reducing the alpha. The most noticeable change is Odin Norge. Being ranked as the fourth best fund using CAPM, the fund is only rank as number eight under the Carhart regression. This could be a result of significant loading on the HML factor, which is not captured under the CAPM, reducing the alpha. Another change is the ranking of index fund PLUSS Index. For this fund, the ranking has changed from 10 to seven, indicating better performance when using the Carhart four-factor model.

Examining the sub-period reveals only small differences between the ranking using the CAPM and the Carhart four-factor model. However, as the ranking changes for almost all funds from time period to time period, using prior performance as an indicator for future performance is not recommend.

TABLE 16: INFORMATION RATIO, CAPM

Ticker	1993-1999	Rank	1999-2005	Rank	2005-2010	Rank	1993-2010	Rank
SKV	0.2933	1	0.3097	2	0.1302	5	0.2213	2
ODN	0.1445	3	0.2516	4	0.0519	12	0.1446	4
PAA	N/A		0.3235	1	0.1628	1	0.2077	3
DHN	0.1413	4	0.1065	7	0.1257	6	0.1131	6
PLA	0.1080	5	0.0369	10	0.1345	4	0.0807	8
HBN	N/A		0.1524	5	0.1622	2	0.1265	5
STBN	0.0822	7	-0.0486	12	0.0997	8	0.0543	9
DNBN	-0.0710	8	0.0050	11	0.0921	9	0.0238	11
PI	-0.0724	9	0.1232	6	0.0679	10	0.0463	10
CNI	-0.1409	10	0.0633	9	0.0620	11	0.0137	12
Ew Cf	0.1057	6	0.0744	8	0.1070	7	0.0918	7
Ew Bf	0.2910	2	0.2672	3	0.1419	3	0.2251	1

The table displays the results from calculating information ratio on all of the funds in the sample using the CAPM.

TABLE 17: INFORMATION RATIO, CARHART FOUR-FACTOR MODEL

Ticker	1993-1999	Rank	1999-2005	Rank	2005-2010	Rank	1993-2010	Rank
SKV	0.2756	1	0.3313	1	0.1303	3	0.1964	1
ODN	0.1116	4	0.1850	4	0.0353	11	0.0438	8
PAA			0.1845	5	0.1523	1	0.1699	2
DHN	0.1479	3	0.1468	8	0.0784	7	0.0587	6
PLA	0.0655	7	0.0741	11	0.1170	5	0.0707	5
HBN			0.1837	6	0.1425	2	0.1195	4
STBN	0.0883	6	0.0284	12	0.0770	8	0.0113	11
DNBN	-0.0899	9	0.0968	10	0.0564	9	0.0066	12
PI	-0.0709	8	0.2023	3	0.0430	10	0.0462	7
CNI	-0.1052	10	0.1543	7	0.0339	12	0.0260	10
Ew Cf	0.0959	5	0.1381	9	0.0798	6	0.0346	9
Ew Bf	0.2638	2	0.2776	2	0.1207	4	0.1276	3

The table displays the results from calculating information ratio on all of the funds in the sample using the Carhart four-factor model.

6.7 Critical remarks

In order to recognize behavioral mutual funds in the Norwegian market, the funds are categorized based on the written statement in which the fund manager induces to utilize "behavioral finance" to make investment decisions. Six mutual funds are identified by reading the prospectuses of the funds, and the investment philosophy of the funds management company. This form of selection involved a lot of subjectivity and may have affected the results due to selection bias. The problem of categorizing funds as behavioral is also mention in the studies of Reinhardt and Brennan (2007) and Wright et al. (2006). One particular problem when categorizing funds, was the case value investing. As described in section 4.2 value investing may be considered both a rational and a behavioral strategy. This implies that different fund managers might have different interpretations of value investing.

The dataset is not tested for the assumptions of OLS estimations, but several studies of the Norwegian fund market have found the market to be free of autocorrelation and heteroskedasticity (Gjerde & Sættem, 1991; Grønsund & Lunde, 2010; Tveito, 2006). However, having not proven the dataset fulfilling the requirements of the OLS estimation, the results must be analyzed with a bit caution.

Using two different models leads to two different results when testing for abnormal performance. As the model of Carhart (1997) is an extended version of the CAPM, I find it more relevant to use the result of this model. The CAPM has also been found to be imprecise and outdated (Montier, 2002). Using R^2 as a measurement of the fit reveals that the model of Carhart describes more of the variability in fund performance through the independent variables, hence, it is a better model when evaluating fund performance.

Further studies on funds with a behavioral strategy may consider interviewing fund managers to better assure that the funds are actually using behavioral finance in their strategy. Another approach could be to use a survey among fund managers in order to categorize funds as either behavioral, conventional or index funds. It could also be interesting to sort all active managed funds according to their loadings on the different factor portfolios. The result could be used to discuss whether the factor loadings are a result of accepting the risk related to the cross-sectional returns, or a result of buying into the behavioral explanation.

7.0 CONCLUDING REMARKS

Given the development of behavioral finance as an alternative theory to the efficient market hypothesis, more and more mutual funds seem to incorporate some sort of filter to capture the effect of irrational traders in the market. Even though behavioral finance has gathered substantial attention in academia, the practical application is still not fully accepted.

Only a few studies have shown interest in the emergence of fund trying to capitalize on behavioral anomalies in the market, and I therefore found it interesting to analyze the performance of Norwegian mutual fund associated with behavioral finance. The objective this study was to examine whether "behavioral" mutual funds in the Norwegian market (1) earned abnormal returns after controlling for risk and (2) had different factor loading on the Carhart four-factor model compared to non-behavioral funds. The behavioral finance funds are identified after a comprehensive review of 67 Norwegian mutual funds using their prospectuses published on Morningstar, and examining the investment philosophy of the funds management company. However, none of the funds in the Norwegian market explicitly admits make investments based on behavioral finance, which caused the categorization to be difficult. I identified six mutual funds that had the strongest characteristics towards a behavioral strategy, and evaluated their performance throughout the period 1993-2010. The models applied were Jensen's Alpha for CAPM and the Carhart four-factor model, Sharpe Ratio and Information Ratio. I also examined the factor loading in the Carhart four-factor model, in order to find differences between behavioral and non-behavioral funds.

My expectations were based on prior studies of behavioral finance funds in the US market, Wright et al. (2006) and Reinhart and Brennan (2007), that found behavioral funds being able to outperform index funds, but not being able to deliver any positive abnormal returns outside the risk factors in Carhart (1997) model.

My empirical results of testing the funds for abnormal performance, using the capital asset pricing model, indicated that some behavioral funds were able to deliver abnormal returns. Skagen Vekst delivered significant alpha at 1% significant level, and Pareto Aksje Norge and Odin Norge delivered abnormal returns at 5% significant level. The result of Skagen Vekst supports prior studies, which also have found Skagen Vekst to perform well (Grønsund & Lunde, 2010; Hoel, 2010; Tveito, 2006). The results show that behavioral funds were able to outperform index fund and conventional funds, in line with the finding of Reinhart and Brennan (2007).

The result of analyzing the funds performance using the Carhart four-factor model indicated that only Skagen Vekst of the behavioral funds were able to deliver significant risk-adjusted abnormal returns. All of the other behavioral funds also had positive alpha-values, but the result did not hold as statistical significant, indicating that the H1 hypothesis fails to be rejected. The conclusion was further supported by the results on the equally weighted portfolio of behavioral funds. These results support the findings of Wright et al. (2006). Since the model of Carhart captures more of the risk related to portfolios, I consider these results to be more robust than the results of the CAPM regression.

Both Share Ratio and Information Ratio displays that behavioral funds were able to outperform index funds. Pareto Aksje Norge (PAA) had the highest Sharpe Ratio, 0.2054, followed by Skagen Vekst (SKV) (0.1907) and ODIN Norge (ODN) (0.1738). The worst performing fund was PLUSS Aksje (PLA) with a Sharpe Ratio 0.098. The market index had a Sharpe Ratio of 0.1112. Information Ratio showed similar results. Best ranked were Skagen Vekst and Pareto Aksje with respectively information ratio of 0.2213 and 0.2077. All of the behavioral funds ranked higher than the matching funds (STBN and DNBN) and the index funds (PI and CNI). The examination of different time intervals also indicates variability in the returns, making it difficult for investors to use prior performance as a predictor of future performance.

The results of examining the factor loadings in the Carhart four-factor model indicated that behavioral funds are more into value investing than conventional funds. However, according to Fama and French (1992) and Lakonishok et al. (1994) value investing could be categorized as a rational and a behavioral strategy. Multiple studies (Barber & Odean, 1998; Kahneman & Tversky, 1979) have found psychology matters in the stock market. The results of this study indicate that mutual funds are still struggling to find ways to capitalize on behavioral finance.

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