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Conditional Mutual Fund Performance in Periods Affected by Market Fear

An Empirical Analysis on Degrees of Active Management and Performance

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Abstract

The engagement around investing in mutual funds is increasing and attracts several personal investors. With previous technological and financial development, there is a wide specter of investment opportunities. Active management is central to the mutual fund distribution, where the distributor charges a fee for professional management. Hence, in combination with market uncertainty, we want to investigate if skilled portfolio managers will exploit opportunities in periods where investors are insecure. This thesis examines whether mutual funds become more actively managed in periods of high VIX values and if they manage to achieve an abnormal return. Findings present changes in the degree of active management where the portfolios are more adjusted to imitate the benchmark index. We fail to deliver statistically significant estimates of positive abnormal return in periods of high market fear. However, we can indicate trends of change to a more passive management strategy where investors should consider passive mutual funds with lower fees.

Keywords – Active management, Mutual fund performance, R^2, Tracking error, Market fear, VIX

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1 Introduction

As the number of private investors in fund and stock markets grows, it is interesting to examine portfolio managers' performance and judgments when the market is affected by a higher level of uncertainty. We can assume that unskilled private investors allocate capital to mutual funds because they lack the knowledge and skills to invest independently. On the other hand, economic intuition may suggest that professional investors make proper investments in undervalued stocks to enhance profits.

This is the origin of our perspective to estimate changes in mutual funds during periods affected by a higher level of uncertainty. The thesis is constructed on the VIX index, where we present VIX values to be classified as high above 29.89 basis points. We define high VIX to represent high market fear. One major remark of our thesis is that we do not conclude with equality between high VIX and crises. Therefore, we strive to analyze periods of high VIX unconditionally to be a crisis.

Our interest is to analyze Norwegian mutual funds with investment restrictions to domestic companies. We want to estimate if mutual funds readjust their portfolio considering high market fear. To measure changes in the portfolio, we will conduct analysis based on R-squared and tracking error methodology. Additionally, we want to see if the mutual funds can gain abnormal returns in uncertain periods. To measure performance, we analyze alpha and differential return.

This arouses curiosity around mutual fund management in periods conditioned on the VIX index. To construct the analysis, we will investigate three constructed research questions. First, we aim to examine what professionals do in these situations. Hence our first research question is: Do mutual funds become more actively managed in periods of high market fear? A change in portfolio construction will impact the fund's performance, which raises two additional research questions. Does a higher degree of active management indicate better performance? Do professional investors increase performance after periods of high market fear?

2 Literature

To construct an empirical analysis, we intend to provide sufficient and relevant literature. This section introduces literature on mutual funds, fund management, and performance. Lastly, we will explain the VIX index and market fear. This chapter will be the framework for the analysis and is necessary for further interpretation of results.

2.1 Mutual Funds

Mutual funds are financial instruments constructed by pooled money from investors on various scales (Investopedia, 2021). Mutual funds invest in stocks, bonds, financial instruments, and other assets. We categorize mutual funds by equity, interest rates, and money markets. Furthermore, we will target equity funds for our analysis when we mention mutual funds. These mutual funds are run by professional money managers and invest in Norwegian equities. The purpose of mutual funds is to be an intermediate where the fund provider charges fees for managing investors' money. In return, investors are given an attractive investment opportunity to increase their wealth. Accordingly, investors benefit from diversification, cost savings, and sharing liquidity risk under economies of scale (Chordia, 1996). As a result of this construction, all the funds' results and expenses are shared by affiliated investors. Mutual funds have gained significant acceptance in households based on the accompanying benefits (Pozen, 2015). Open-end funds make it convenient for investors to sell their holdings daily and use professional investment management. The aspect of diversification is more than investing on your own and might be a reasonable investment regarding periods of high market fear and economic downfall.

2.1.1 Mutual Fund Management

One reason for charging fees when investing in mutual funds is because portfolio managers run them. Managers have two different ways of managing mutual funds: actively or passively (Barclays, 2021). The research concentrates on actively managed mutual funds through the analysis, where the portfolio manager performs a more comprehensive market analysis for a more significant fee. We will not explain the costs in detail, but it is necessary to be aware of them since investors have alternative investment options in passively managed mutual funds. These passive investment opportunities can be used as an alternative cost of active management (Malkiel, 1995). The passive funds might not exceed the market in returns, but generate a return equal to the market. Therefore, the fees linked with these funds are drastically lower.

One of the most important aspects of mutual funds is that investment mandates limit portfolio managers (Vogt, 2021). These mandates place restrictions on how the fund is managed. For example, there may be restrictions on share weights or conditions in the form of a minimum number of shares or cash holdings. These investment mandates create boundaries and influence their investment strategy. Therefore, when assessing fund portfolios, it is crucial to be aware of the mandates. These two types of mutual funds differ in several areas, including management, costs, and most excess returns.

Passive management

A passively managed fund consists of a portfolio that tries to mimic the benchmark in terms of risk and return. As a result, the portfolio will have the same securities and be weighted equally as the benchmark. These funds can be interpreted as index funds which can enlighten the market activity. Small fees provide appealing investment opportunities. Managers for passive mutual funds track the movement of the market they are replicating (Barclays, 2021). Passive management and index funds with the average return are commonly used as benchmarks for actively managed funds (Del Guercio & Reuter, 2014).

Active management

For our analysis, we will solely examine actively managed funds. Banks and other financial institutions provide these funds. According to the prospectus, teams of portfolio managers have constructed the fund and further contribute with surveillance and monitoring daily. Higher fees are justified by deeper market analysis with an actively managed portfolio to exploit opportunities that might result in excess return compared to the benchmark. Kosowski et al. (2006) and Barras et al. (2010), assumes that mutual funds can generate an excess return, at least before fees caused by skills. This implies that active strategies by professional managers shall outperform passive alternatives (Reibnitz, 2017).

Despite opportunities for abnormal returns, the risk increases significantly since the fund's portfolio deviates from the benchmark. Portfolio managers consistently exceed the benchmark, which involves deviation from the reference index in stock picking. The managers usually act on mispricing in the market and seek returns that exceed the market (Sharpe, 1991). The investor who invests through actively managed mutual funds will receive professional stimulation in stock picking, which might overtake their stock-picking ability.

2.1.2 Measurement of Management

Actively managed mutual funds will invest in many of the same shares as the benchmark. How can we examine the degree of active management? Actively managed funds' will differ from the benchmark. The report, assembled by Bjerksund & Døskeland (2015), on behalf of The Norwegian Consumer Council, shed light on three metrics and assess a professional framework for examining the extent to which funds are actively managed. Metrics of measurement could be R-squared[1], where we can measure variations in returns of the fund up against interpretation in returns of the benchmark. A high degree of R^2 would indicate highly correlated returns between the fund and benchmark. Implicitly, it states that the portfolio consists of the same stocks where a high degree of R^2 brings suspicions of passive management.

Active share is another measure of active management. The method implies a percentage of the consisting portfolio differs from the benchmark portfolio. Active share looks directly into the two different portfolios to compute the weight of a stock in both portfolios. For using this metric, it is necessary to have information about the equities included in the portfolio. Unfortunately, we do not have the opportunity to extract this information from our data sources. However, it implies a framework for further argumentation about active management.

[1] R-squared.

A third metric is tracking error (TE), which can distinguish divergence between return behavior of both portfolios. For example, high TE may indicate outperformance of benchmark by having lofty variance indifference of return. In other words, high TE signals an active management strategy.

2.1.3 Mutual Fund Performance

Since there are two ways of managing mutual funds, different performance levels and returns are actual. Neither active nor passive management can forecast future success. The latter represents lower volatility and more consistent performance over time. Actively managed mutual funds are exposed toward stock-picking by portfolio managers. Therefore, they may have higher risk since stock-picking away from the benchmark often results in investments in companies qualified as small-capitalization companies. The performance of an actively managed mutual fund would, to a higher degree, rely on the manager's skills. Less skilled portfolio managers would tear the performance of the actively managed fund on a bigger scale than natural adjustments in the market for the passive mutual fund. Hence, the degree of active management directly affects the performance of the fund.

The performance of an actively managed fund and benchmark would need to be corrected for variables, so ground pillars for performance are mutual to conduct a careful comparison. Such variables are beta values which represent exposure for risk. Jensen's alpha can extract the return of a fund and correct for the difference in risk. According to Jensen (1967), we can measure performance more correctly since their return is adjusted for different risk exposures. Actively managed funds are more skilled in gross alpha (Crane & Crotty, 2018). We aim to measure performance by ordinary alpha. According to Fama & French (2010) and Carhart (1997), comparing funds by their factor models is possible. These theories bring performance as a reasonable measurement and quantify direct differences.

2.2 Benchmark

The Norwegian Fund and Asset Management Association has industry recommendations that guide Norwegian fund management when choosing benchmarks. For a mutual fund to select the correct benchmark, the guidelines recommend finding a reference where both mutual fund and benchmark are associated with the same investment universe. In addition, the benchmark should be investable, so the reference is a real investment opportunity on behalf of the mutual fund. Further, the benchmark methodology should be recognized within, for example, valuation and weight restrictions. Other factors that the benchmark should be comparable to the mutual fund would be taxes and dividends, reliability and independence, availability, and historical prices (Verdipapirfondenes forening, 2019).

We need a unit of measure when referring to excess return and performance measurement. We will use OSEFX as a measure that can reference fair return and opportunity cost since it is the standard benchmark for all included mutual funds. Risk-adjusted return between the funds and benchmark indicates performance and will be used to measure this (Beber, 2021). The benchmark would represent a weighted portfolio within the same market. Restrictions for choice of funds are domestic investments located in Norway. Implicit funds invested in OSE noted stocks and benchmark obligated to consist of corresponding stocks.

2.3 VIX Index

VIX is an index computed by the Chicago Board Options Exchange (CBOE), derived from prices at a panel of options contracts on the S&P500 index. The principle of the VIX index is to identify market uncertainty among investors (Chen et al., 2021). The outcome from the index is to visualize what the investors, in general, feel implicit about the market. Our analysis will determine a specific point on the VIX index, which defines high VIX values. The VIX index increasing and reaching the determined point indicates abnormally high uncertainty. The definition of high VIX is essential for determining which periods to include in our analysis. The exciting view at VIX is that it reflects the uncertainty perception by all participating investors. We evaluate the appearance of the market, reflecting a high level of uncertainty between investors to be classified as high market fear. We assume that a market where investors are highly uncertain about the future and adjust their portfolio to a more extensive cash holding or investments in safer assets indicates fear among participating investors. A vital remark to our definition and baseline for the thesis is that we do not conclude with similarities between a crisis and high VIX. We will define high VIX values to see the actual changes in mutual funds caused by VIX values before extracting the respective periods. We include the periods before and after high VIX to assemble a reference for market behavior without high fear.

2.4 Market Fear

Having positions in the market may affect investors' risk exposure and the psychological effect of influencing decision-making. Buying stocks as a private investor can initially be a short-term or a long-term investment. However, mutual funds often have a long-term investment horizon (Vogt, 2021). This horizon might be reduced for mutual fund investors in the aspect of the psychological effect. Nevertheless, both private investors and professionals are still affected by the psychological factor. This arouses the exciting view of professional management of mutual funds in periods affected by high market fear. We want to analyze mutual funds' historical data and past behavior to generate assumptions for similar future situations with high VIX. According to portfolio manager Vogt (2021), the market often holds a position where the securities are overpriced longer than underpriced. We will investigate if portfolio managers can enhance their portfolios in periods caused by high market fear. If the market participants are insecure about the future, we can see an increase in VIX and assume high market fear. It might bring opportunities for professional investors to discover oversold securities. We find it interesting to take advantage of these situations and examine what the experienced portfolio managers implement in their investment strategy under their limited investment mandates.

3 Main Issue and Additional Research Questions

3.1 Main Question

The previous period, which was influenced by Covid-19, saw the all-time highest VIX value on 03.11.2020 (82.69). The VIX index can indicate the market fear and is based on investors' actions in the financial markets. VIX is negatively correlated with the stock market, and high values often indicate declining stock prices (Henricks, 2021). A high VIX suggests that investors are skeptical and adjust their portfolios due to this skepticism. On the other hand, a high VIX may propose opportunities for professional investors to exploit opportunities in underpriced securities when investors reflect a bearish view of financial markets, which brings us to our primary study question:

Do active mutual funds become more actively managed in periods of high market fear?

The literature on active management focuses mainly on how large and well-managed the funds are. We desire to investigate what happens in the mutual fund managed by professional investors when a market situation with high VIX values occurs. Will professional investors deviate from the benchmark and take positions that qualify the fund for more active management in periods where bearish investors dominate the market? This will be the essence of our methods and evaluation in making a statement regarding active management during heightened market panic.

3.2 Additional Research Questions

In addition to the degree of active management, we want to investigate the mutual funds' performance caused by the managers' decisions. This forms our additional research questions:

- Does a higher degree of active management indicate better performance?
- Do professional investors increase performance after periods of high market fear?

4 Data

This chapter will, at first, introduce our collected data and the variables upon which the analysis is based. Then, we will explain how we gathered the data and how we will utilize it and build the data sample. As a result, despite various observations, we have cleaned the unbalanced dataset and ended up with a sample selection that produces estimates to answer our research questions.

4.1 Data Sample

For our analysis, we have collected data from Bloomberg Terminal. Our sample consists of the VIX and OSEFX indices and 9 Norwegian mutual funds investing in Norway. An unbalanced dataset has been compromised by omitting values of NA[2], where the effect is a dataset with an equal number of observations for each variable. The dataset is constructed on daily observations to obtain more accurate estimates to identify periods of high market fear. In the regression, we have used factor models computed by professor Bernt Arne Ødegaard from the University of Stavanger (Ødegaard, 2021).

4.1.1 Time-period

Correction for NA's makes it possible to analyze daily data observations to address more accurate periods of high market fear. Our panel data includes both time-series and cross-sectional data. The time-series spans from January 2006 to November 2020, where we assume to have 250 trading days each year. The intention is to have a data sample to collect major historical events that are still current and do not represent obsolete information. This refers to technological development, new regulations, and asset management strategies. We will examine the whole time-period, the periods of high market fear, and before and after high market fear. One period will consist of the latter three periods. These are referred to as ex-ante, event, and ex-post. We will investigate each period closely. The periods will stretch over time to occur in various months for the different periods.

[2] NA - not available.

We can view the whole time-period as an overall look over almost 15 years. We dig deeper into periods that might not be qualified as crises for the analysis. Yet, the market interacts with high market fear. These period withdrawals from the full-time frame would be essential for the investigation to examine portfolio managers' behavior.

4.1.2 Population in Data Sample

The analysis accounts for a population of 9 different mutual funds, which all meet our set obligations.

- Equity fund
- High market cap
- Invest in Norway
- Well known distributor
- Not limited to investing in a specific sector
- Been actively managed and operated through the whole time-period

Our population is selected to present the widespread of mutual funds with an equal geographical investment universe. These nine mutual funds invest in Norway, where some focus on value stocks while others are more positioned against growth stocks. The sample of mutual funds creates a general assumption of the behavior of similar funds. Limiting the data sample to nine mutual funds allows for a further in-depth analysis instead of presenting the results of all possible funds.

The population of mutual funds which meets the requirements is selected randomly to avoid selection bias. Mutual funds presented in the data sample are a variety of mutual funds investing in Norway with different forms of strategy and size. The variation visualizes the various investment strategies and behavior in periods of high fear. The analysis will utilize the small sample size and concretize behavior a mutual fund investor can expect.

4.1.3 Descriptive Statistics of Dataset

The collected data are daily NAV's[3] of the different mutual funds and OSEFX. To compare and analyze the mutual funds, we are not interested in the value of the mutual fund but the change in returns. Therefore, our daily returns are derived as:

$$r_{i,t} = ln(\frac{NAV_{i,t}}{NAV_{i,t-1}}) \tag{4.1}$$

This return reflects today's return relative to yesterday's return. We choose logarithmic returns because it has abilities that correspond to the abilities of normally distributed variables (Døskeland, 2014). Log returns are also time-additive, meaning that we can add them across time to get the total return over a specified period.

4.2 Variables

To understand what drives the mutual funds' active management, we need instruments that measure their performance and degree of active management. Our calculations are based on the net asset value of the different mutual funds converted to logarithmic returns. Variables promote empirical evidence and conclude the analysis with a more significant effect. Our selected variables for the analysis are presented in Table 4.1.

Table 4.1: Descriptive Statistics

Variable	**Number of observations**
Alfred Berg Gambak	3909
Danske Invest Norge Vekst	3864
DNB Norge A	3866
Eika Norge	3871
KLP Aksje Norge	3795
Nordea Avkastning	3866
Pareto Aksje Norge B	3844
ODIN Norge C	3909
Storebrand Norge A	3908
Oslo Exchange Mutual Fund Index	3901
CBOE Volatility Index	3812

[3] Net asset value.

Henceforth these variables will be referred to by the name of the distributors. See appendix A1 for further descriptive statistics of the variables.

4.2.1 Dependent Variable

The funds' performance will be the dependent variable to measure the affection of changes in portfolio composition. We will use the funds' log return as a measure of performance. The differences between the return of the mutual funds and the benchmark will determine the level of performance. As illustrated in Equation 4.1, the return is based on NAV prices of the funds over time. The reason for choosing this as a dependent variable is that this is the only instrument representing mutual fund management. The funds are constructed and managed to make money and capitalize.

4.2.2 Independent Variables

A mutual fund's performance in excess returns depends on several variables, such as fees, portfolio team, and strategy. For our analysis, it is not interesting to investigate and dig deep into such factors, but rather examine the most prominent empirically proven variables. Nevertheless, factors in small and large companies with capitalization and high and low book-to-market value are central to financial theory. Therefore, we will conduct regressions concerning these factors in addition to momentum. These factor models function as independent variables to understand the market exposure to the portfolio and their impact on performance and will be specified in more detail in Chapter 5.

4.2.3 Risk-free Rate

One-month NIBOR extracted from Bloomberg Terminal will estimate our risk-free rate. Since the dataset is based on daily observations, we will transform the one-month rate to a risk-free daily rate over 250 trading days.

$$r_f = (1 - NIBOR)^{(1/250)} \tag{4.2}$$

The risk-free rate is provided through NIBOR as a proxy for an investment without risk. It is also needed when calculating the expected market premium. This will be the premium for having a portfolio exposed to market risk.

$$E_{(Rp)} = (r_m - r_f) \tag{4.3}$$

These measures are included to construct our analysis and derive a performance measurement.

4.3 Data on Periods of High Market Fear

For the unique periods with high VIX, we have computed a decile to determine what we can categorize as high market fear. The periods are extracted because of uncertainty and not due to a crisis. We have two periods that classify as crises, one of them based on the financial structure in the world, and two more periods where market participants indicate an irregular level of uncertainty and fear.

4.3.1 Period 1

The first period of our analysis is 18.12.2007 – 14.12.2009, which is classified as the financial crisis. The period is extracted due to values on the VIX index and not the classification of a crisis. The crisis was still ongoing after this period, but option trading prices in the US showed less market fear and are therefore not included in the analysis.

4.3.2 Period 2

The second period of our analysis is 05.03.2010 – 30.08.2010. This period will still be classified as a recession if one looks at the market situation with, for example, still-high unemployment. Despite this, the financial market steadily grew and almost returned to the same level as before the crisis. Therefore, this represented period does not reflect a crisis for the thesis since the financial markets showed more remarkable results. However, there are still reports of unusually high VIX estimates that classify the period in the analysis.

4.3.3 Period 3

The third period, 19.05.2011 – 27.12.2011, is not classified as a crisis but can be related to high VIX values.

4.3.4 Period 4

Finally, the period 16.12.2019 – 15.07.2020, caused by Covid-19, will be included. This crisis is a different type of crisis than the financial crisis. Where financial institutions were the problem at the time, they are now trying to fix the crisis. As a result, abnormally high VIX values have been observed and classified as the period included in our analysis.

5 Methodology

This chapter will present the models used in our analysis to explore and answer the research questions introduced in Chapter 3.

5.1 Management

This section presents the instruments used to measure active management. We define the degree of active management as a deviation between the funds' portfolio and the benchmark portfolio.

5.1.1 Differential Return

The mutual fund portfolio will consist of various stocks selected by the team responsible for the fund. The mutual fund and benchmark will have a return of R_P and R_B, respectively, equal to the total return for all the different stocks within the portfolio. The mutual fund can invest in N different stocks where the individual stock's return is equal to R_i. The fund will have a total cash holding where the holding can be invested with different weights in the various stocks. The weight in stock i of portfolio P will be noted as $w_{P,i}$. The total weights invested in stocks and cash holdings must equal 1. The differential return, or active return (R_A) is the difference between the return on the portfolio R_P and the return on the benchmark index R_B.

$$R_A = R_P - R_B \tag{5.1}$$

Therefore, the difference in net return between portfolio P and benchmark B indicates active management in portfolio A if there is a difference in benchmark-adjusted return (Cremers et al., 2016). The active portfolio's weights for stock i are $w_{A,i} = w_{P,i} - w_{B,i}$. The actively managed portfolio will be a redistribution from portfolio B to portfolio P.

The differential return will therefore be the return on portfolio A:

$$R_A = \sum_{i=1}^{N} w_{A,i} R_i \tag{5.2}$$

This equation indicates that if the weights of portfolio A, which is actively managed, are consistently zero for all the stocks, then the differential return equals zero. A necessary condition for a positive or negative differential return is that the fund deviates from the benchmark index. Therefore, the greater the differences between the portfolios, the greater the differential return will be, both positively and negatively (Bjerksund & Døskeland, 2015).

5.1.2 R-squared

R^2 is the fraction of the sample variance of the dependent variable Y explained by the regressors in a regression model (Woolridge, 2013). In other words, R^2 measures how much of the mutual fund's return can be explained by the independent variable or variables in the model. The R-squared ranges between 0 and 1. An R^2 near 1 indicates that the regressors are good at predicting the dependent variable. In contrast, an R^2 close to 0 indicates that the regressors are not very good at predicting Y. A high R^2 indicates a portfolio that replicates the benchmark. Conversely, a lower R^2 suggests a portfolio that deviates more from the benchmark, expressed as a more actively managed mutual fund. The relationship is described mathematically as follows:

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{5.3}$$

SS_{RES} = *Sum of squared residuals. Represents error term* ϵ_t
SS_{TOT} = *Total sum of squared*

5.1.3 Tracking Error

Tracking error is a well-established measure of active management. The instrument reflects the fluctuations in the fund's active return over time. Tracking error expresses the deviation in the composition of the funds relative to the benchmark index, and the covariations and fluctuations in the stock return in the market (Bjerksund & Døskeland, 2015). The relationship is expressed as:

$$TE = \sigma(R_P - R_B) \tag{5.4}$$

A high tracking error estimate would indicate a high variance of the difference in the returns of the two portfolios (Hwang & Satchell, 2001). Therefore, a high TE estimate suggests a more actively managed portfolio than a portfolio with a low TE estimate. We will use calculated average TE estimates in Table 6.3 as a benchmark for indication of high and low TE measures. On the other hand, a fund with a low TE estimate will have a portfolio that is around as volatile as the benchmark portfolio, indicating that the manager closely follows the benchmark.

Since TE is a relative volatility measure, it can change during periods of higher VIX without any changes in the portfolio. In addition, the tracking error implies a range of possible outcomes for the portfolio. Therefore, a higher TE will indicate better conditions for a good portfolio manager, where his skills will generate higher returns. Conversely, if the portfolio manager operates poorly, the mutual fund will experience greater losses than the benchmark index.

5.2 Performance

To better understand and answer the research questions, we must measure the performance of the funds. There are several ways to do this. To examine how well a mutual fund performs, we need to take into consideration factors that may explain this. There are several explanatory factors to include in an analysis of performance. To limit our analysis, we will focus on the daily return within the same investment universe by factor models introduced in 5.2.2.

5.2.1 Regression

Methods presented by Dougherty (2002) describe theoretical concepts for measuring changes in return using explanatory variables. By implementing a linear regression analysis, we can investigate the effect of changes in explanatory variables on the dependent variable.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_i X_i + ... + \epsilon_t \tag{5.5}$$

where,

Y *= Dependent (explained) variable*

X_i *= Independent (explanatory) variables*

β_0 *= Intercept, represent a constant term, also known as alpha (α)*

β_1 *= Slope coefficient, which measures the change in Y by one unit of change in X_1 holding other explanatory variables constant (X_2 and X_i)*

ϵ_t *= Stochastic disturbance term. Collects factors which are not included as explanatory variables but influence the dependent variable*

This method is frequently used. According to Doughery (2002), OLS estimates are the most efficient if the Gauss-Markov conditions are satisfied. OLS tries to fit the data into the regression as accurately as possible by minimizing the sum of squared residuals. If the assumptions provided by Gauss-Markov are violated, biased estimators and inconsistencies will occur (Stock & Watson, 2020).

5.2.2 Factor Models

We will utilize statistical regression and asset pricing models to generate output for the analysis. The factor models can create a regression model that explains performance relationships and changes in return relative to risk.

Capital Asset Pricing Model (CAPM) is built upon earlier work from Harry Markowitz around modern portfolio theory in 1952, which focused on the key element diversification. The individuals who introduced us to CAPM individually by further building on Markovitz's ideas were Treynor (1961, 1962), Sharpe (1964), Linter (1965a, b), and Mossin (1966). CAPM is used for pricing risky securities with respect to risk-free rate (r_f), market risk premium ($E(r_m)$ – r_f), and the security's exposure to systematic risk compared to the market (β).

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f] \tag{5.6}$$

As an economic equilibrium-based model, CAPM makes it possible to compute a stock's expected return. The model is commonly used because of its simplicity. However, there are certain drawbacks to the model. Where investors are risk-averse and strive to maximize utility from their investments, there are issues with establishing competitive and efficient securities markets. For example, if investors could accurately estimate cash flows and identify the value of a stock, CAPM would not be necessary (Bossaerts, 2003).

In contrast, we have Jensen's single-index model (1968), which reflects the risk-adjusted performance. The SFM[4] assumes there only is one macroeconomic factor responsible for systematic risk, which is reflected in a market index. Utilizing the model will compose the expected excess stock return due to firm-specific factors denoted by the alpha coefficient (α). Due to firm-specific risk, the intercept will present abnormal return indifference from market events. The single-index model is as follows:

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + \epsilon_i \tag{5.7}$$

Jensen's alpha can describe the abnormal return mutual fund managers achieve but receive criticism for including only one risk factor. Implications are concerned with the model because it only considers the market as a risk factor and cannot accurately capture cross-sectional differences in returns (Fama & French, 1992).

[4]Single-factor model.

Fama & French (1992) presented a cross-section of average returns on US stocks to show little relation to the market and consumption β (Sharpe, 1964; Lintner, 1965; Breeden, 1979) asset pricing model. They introduced new variables for asset pricing theory which increased explanation power to the cross-sectional average returns. This was the origin of the Fama & French Three-Factor Model. The newly formulated regression is expressed as:

$$r_i - r_f = \alpha_i + \beta_m(r_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_i \tag{5.8}$$

Looking deeper into Fama & French (1992), it is clear they have been inspired by Banz (1981), as he finds empirical contradictions to the Sharpe-Lintner-Black model in terms of size. The market equity adds to the cross-sectional average returns. Small stocks (low ME[5]) have too high average returns, while large ones (high ME) have too low average returns. This is the origin of the factor SMB[6]. Furthermore, Stattman (1980) and Rosenberg et al. (1985) have empirical evidence of a positive relationship between the average return on U.S. stocks and the ratio of a firm's book value of common equity.

Additionally, Lakonishok et al. (1991) found that book-to-market equity has a significant role in explaining average Japanese stock returns. This was the origin of HML[7]. The previously mentioned literature is the basis of the three-factor model. With SMB and HML, Fama & French argues for enhancing the single-index model's ability to reflect a stock's variation in return. This work by Fama & French is the resurrection of Carhart's four-factor model:

$$r_i - r_f = \alpha_i + \beta_m(r_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{PR1YR}PR1YR_t + \epsilon_i \tag{5.9}$$

Having absorbed inspiration from Fama & French (1993) and further implemented another factor, momentum, these four factors suggest that they may explain even more cross-sectional variation in average return on stock portfolios (Carhart, 1997).

[5] Market Equity.
[6] Small-minus-big market capitalization.
[7] High-minus-low book to market value.

The additional factor PR1YR represents one-year momentum in stock returns. PR1YR[8] is constructed as the equal-weight average of the top 30% eleven-month return minus the bottom 30% eleven-month return, both lagged by one month. We consider the four-factor model to explain significantly more variation in return. Hence, it will be used directly in our analysis due to its ability to make more interpretations. The return which the model does not explain will be captured in the stocks' alpha (α), represented as an abnormal return.

5.2.3 Alpha

Having two different portfolios makes it possible to investigate the deviation between their respective differential return. The differential return struggles to measure actual performance adjusted for risk. There might be a substantial risk deviation, so comparing the portfolio's differential return may not give reliable results. We are interested in abnormal returns after adjusting for risk in both portfolios to reflect actual performance. Hence, we are interested in the mutual funds' alpha, which is the excess return we get when we adjust the market to the beta risk that the fund has. It is essential with a unit of measure to reveal the result of management decisions made during high VIX periods. The utilization of alpha will be an estimate for identifying actual results.

5.3 Defining High VIX

Since we do not have any clear definition of a market embossed by fear, we must compute the limits for high VIX classification. Hence, we apply a statistical calculation to define high VIX parameters. We can constrain our dataset in central periods using the formula below for further analysis. The proportion of the data sample which qualifies as high VIX periods will be the center of attention.

[8]Momentum.

$$n = 1_a, 2_b, 3_c, ..., n_x \tag{5.10}$$

$$q * (n + 1) = k, \text{ where } 0 < q < 1 \text{ and } 0 < k < n$$

where,

q = *Decile percentage*

n = *Number of observations*

k = *Maximum row number for decile limit*

For the analysis, VIX is either high or low. The main focus is on the events of increased market fear. However, for comparison, we present a period before and after the events with the same amount of observations.

From Equation 5.10, we can determine the decile which classifies high VIX. Furthermore, the data sample must be sorted from lowest to highest values where each observation will be numbered n_x. The factor q represents the decile limit percentage. The outcome from the calculation of k is a specific observation in the number series, which represents the maximum limit within the chosen decile. The remaining observations have values higher than the represented decile. These are interesting for our research.

5.4 Statistically Significance

An important aspect of the thesis will be to investigate whether the changes in alpha and R-squared in periods of high market fear are statistically significant. If the changes turn out to be significant, it can be argued that there is a change in these values during periods of high market fear that are not due to coincidences. This will strengthen any findings in the thesis. To investigate this, we use a Z-test, a type of hypothesis test that tests whether two populations have different means when the variance is known, and the sample size is greater than 30 (Investopedia, 2021). The z-statistics in the test follow a normal distribution. We will run the Z-test for the event periods within our four periods.

The sample's mean is the mean alpha (R^2) within the event period. The population's mean is the mean alpha (R^2) in the entire sample period. The population's standard deviation is the fund's standard deviation in the entire sample period, while the number of observations is the number of observations within each event period.

The z-statistics for the alpha Z-test are derived from the following equation:

$$Z = \frac{\bar{\alpha} - \alpha_0}{\frac{\sigma}{\sqrt{n}}} \tag{5.11}$$

where,

Z = *z-statistic*

$\bar{\alpha}$ = *mean of sample*

α_0 = *mean of population*

σ = *standard deviation of population*

n = *number of observations*

The z-statistics for the R^2 Z-test are derived from the following equation:

$$Z = \frac{\bar{R^2} - R_0^2}{\frac{\sigma}{\sqrt{n}}} \tag{5.12}$$

where,

Z = *z-statistic*

$\bar{R^2}$ = *mean of sample*

R_0^2 = *mean of population*

σ = *standard deviation of population*

n = *number of observations*

We want to find the corresponding p-values given from the z-statistics. Regarding the cumulative distribution function (cdf) to the standard normal distribution, which is commonly denoted by Φ, the p-value is provided through the following equation:

$$p - value = 2 * \Phi(-|Z == score == |) \tag{5.13}$$

6 Findings

In this chapter, we present an outline highlighting the most important and interesting findings.

6.1 Periods Defined by High VIX

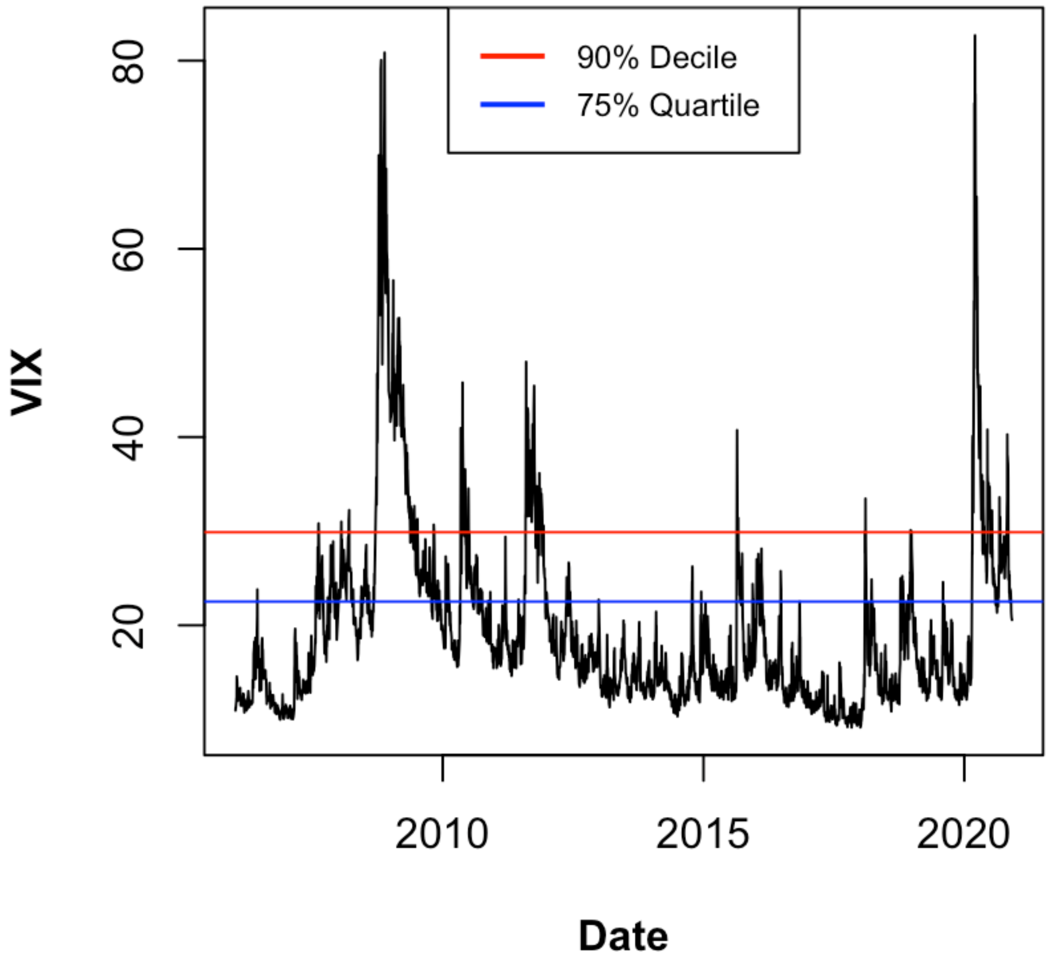
Our thesis will go through the aspect of investing in the market, which implies risk exposure and volatility. Further, it is interesting to investigate decisions conducted in periods affected by a high level of uncertainty. Our research considers abnormal high VIX values to correspond with high market fear. We will divide the last 15 years of VIX values into deciles to specify periods that classify to be periods of high market fear. Further, the selected periods will be analyzed to see how active management and performance change.

6.1.1 Presentation of VIX Index

In the previous chapter, we presented the methodology for defining high VIX. The formula divides the VIX into ten equal weights to find the maximum limit for chosen decile. We must have a decile to classify VIX values as abnormal high in a sufficient amount of time. It would not be sufficient with high VIX values lasting in a short period since it might not affect the portfolio composition. VIX values must be extraordinarily remarkable in total for defining adequate periods. Calculations limit the decile to be represented at 90%. Values more prominent than the 90% decile will be the estimation area, and periods within are withdrawn for further research. Computed by the formula in Chapter 5, results show that VIX values are determined high after the index reaches 29.89 basis points.

Figure 6.1: Historical VIX Prices with 90% Decile

The figure shows the VIX index and its movements throughout the sample period (2006 to 2020). The time-period is expressed through the horizontal axis, and the VIX price is expressed through the vertical axis. The black line represents the VIX values in our trial period. The blue line represents a 75% quartile, while the red line represents a 90% decile.



Above, we have visualized the VIX index and its movement over the last 15 years. From Figure 6.1 it can be identified that a quartile of 75% would be insufficient since it would capture excess observations and inadequate estimates to define high market fear. Further, Figure 6.1 visualizes that a decile of 90% would represent a more suitable and sufficient limit. The remaining observations above the 90% decile contain 10% highest VIX values and are attractive for further analysis. As visualized in Figure 6.1, there are 12 periods potentially classified for the analysis. However, we focus our attention on four periods with sufficient observations, where average VIX values are classified as high for a minimum of one month.

Average high VIX over one month is an adequate time-period since the portfolio manager has time to adjust the portfolio. It indicates the market to be uncertain consistently over 8% of a year. Among these, we have two periods defined as crises, while the remaining two are classified as periods of high market fear. As earlier introduced, our primary focus of the analysis is generally market fear, not crises in particular. However, it is interesting to see differences between a period characterized as a crisis and a period only affected by high market fear.

Table 6.1: Average VIX Within Each Period

	Ex-ante	**Event**	**Ex-post**	**Date Span**
Period 1	23.13	48.25	25.57	18.12.07 – 14.12.09
Period 2	17.69	31.64	24.92	05.03.10 – 30.08.10
Period 3	19.13	36.47	29.25	19.05.11 – 27.12.11
Period 4	15.04	48.79	30.23	16.12.19 – 15.07.20

6.2 Entire Sample Period

To estimate the actual effect of market fear, it is essential to have a reference of the entire period. This time-period will depict the mutual fund's overall management and performance. It will provide an overview and may assist in interpreting the fund's behavior.

6.2.1 Exposure to Factors

Table 6.2 reflects the overall active management in the form of R^2 and the abnormal return achieved after adjusting the risk equivalent to the benchmark for the whole time-period. Henceforth we will base our analysis on FFC[9].

[9] Carhart four-factor model.

Table 6.2: Full-time Period FFC Output

The table shows the mutual funds' R-squared, annualized alpha, and risk factor coefficients throughout the entire sample period (2006 – 2020). The alpha and R-squared values are in percent. The table is ranked by the funds' R-squared, from lowest to highest R^2 value. The bottom row shows the average R^2, alpha, and beta coefficients. The values in parenthesis are corresponding t-statistics. Significance levels *p <0.1; **p <0.05; ***p <0.01.

	R^2	α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}
ODIN	76.7%	-1.16%	0.73***	0.19***	0.10***	0.02**
		(-0.49)	(85.02)	(16.42)	(10.60)	(2.05)
Storebrand	84.9%	1.35%	0.98***	0.04***	0.00	0.02
		(0.49)	(98.30)	(3.31)	(0.01)	(1.32)
Pareto	86.5%	1.31%	0.85***	0.13***	0.09***	-0.02**
		(0.62)	(111.86)	(13.10)	(10.09)	(-2.10)
Alfred Berg	89.5%	2.51%	0.92***	0.13***	-0.00	0.11***
		(1.26)	(128.16)	(14.13)	(-0.45)	(13.54)
Danske Bank	89.5%	2.92%	0.87***	0.12***	-0.00	0.01*
		(1.53)	(127.08)	(13.66)	(-0.05)	(1.79)
Eika	94.0%	-0.39%	0.91***	0.09***	0.03***	-0.02***
		(-0.26)	(168.88)	(12.09)	(4.45)	(-3.50)
Nordea	96.0%	0.90%	0.97***	0.07***	0.02***	0.00
		(0.69)	(206.21)	(11.38)	(3.76)	(0.14)
KLP	96.8%	0.75%	0.96***	0.07***	0.04***	-0.01**
		(0.65)	(233.01)	(13.67)	(7.73)	(-2.56)
DNB	97.5%	-0.53%	0.98***	-0.01	-0.01**	-0.00
		(-0.47)	(252.03)	(-0.97)	(-2.21)	(-1.04)
Average	90.2%	0.85%	0.91	0.08	0.02	0.01

The table presents the deviation between the mutual funds for the last 15 years. We can extract that ODIN has maintained the lowest R^2 value throughout the research time. Eika is the only mutual fund we can present statistically significant values for all four factors at a 1% significance level.

Further, the table presents significant values for the whole population in the market coefficient factor. Although the alphas of Danske Bank and Alfred Berg are among the highest, neither of the distributor's R^2 is among the lowest. Their R^2 is lower than the average R^2 and has a higher alpha than average. Nonetheless, the degree of active management in these funds was higher than numerous other funds, which may explain the disparities in alpha. Interestingly, the mutual funds KLP, Nordea, and DNB have active management degrees of less than 5% based on R^2 and are classified as actively managed mutual funds.

6.2.2 R-squared and Tracking Error

In the previous table, we introduced R^2 over the whole sample period. Although the table implies active management, it may not be sufficient to base the mutual fund's active management on R^2 solely. Both approaches displayed in Table 6.3 can indicate various sorts of active management and provide alternative interpretations of how mutual funds are managed.

Table 6.3: Full-time Period R-squared and Tracking Error

The table shows the mutual funds' R-squared and tracking error throughout the entire sample period. All values are in percent. The table is ranked by the funds' R-squared, from lowest to highest R^2 value. The bottom row shows the average R^2 and tracking error value.

	R^2	TE
ODIN	76.7%	13.21%
Storebrand	84.9%	10.25%
Pareto	86.5%	9.78%
Alfred Berg	89.5%	8.71%
Danske Bank	89.5%	8.66%
Eika	94.0%	6.58%
Nordea	96.0%	5.17%
KLP	96.8%	4.76%
DNB	97.5%	3.97%
Average	90.2%	7.90%

Table 6.3 demonstrates that a lower R^2 results in a higher TE. Because the TE gauges return volatility, it is vital to consider that TE can change without adjusting the portfolio due to higher market volatility.

The table may also visualize different investment strategies within active management. A mutual fund's composition and investment strategy are crucial in the form of what to expect in return. Mutual funds with a lower degree of active management might have a greater intention for imitating benchmarks. DNB has an R^2 of 97.5% and invests more passively, closer to the benchmark. The more actively managed fund ODIN has an R^2 of 74.4% and is more likely concentrated toward small-capitalization stocks. In Table 6.2, we can see their exposure against factor SMB is confirmed with the highest estimate of the sample at 0.19.

Outcomes from being more actively managed will unfold in returns. Good stock selection excluded from the benchmark portfolio may increase the actively managed fund's return relative to the benchmark index. If the manager fails to pick good stocks, the return will suffer on a larger scale, and imitating the benchmark will be more sufficient. Therefore, active management is critical to the mutual fund's performance and has a more significant impact than the simple return of a stock included in the benchmark. This influence is the interesting part of investigating further. How does the degree of active management change during instances with high market fear? Is the mutual fund's portfolio team implementing a more aggressive investment approach, attempting to capitalize on opportunities when other investors are uncertain, or is it adapting to the market and limiting potential losses?

6.2.3 Alpha and Differential Return

The yearly differential return is visualized in Table 6.4. More than half of the randomly sampled mutual funds have performed better than the benchmark during the entire period. The differential return indicates the deviation in return between mutual funds and benchmark. This is a key figure for portfolio managers when measuring their success against competitors.

Table 6.4: Full-time Period Annualized Alpha and Differential Return

The table below shows the mutual funds' annualized alpha and differential return throughout the entire sample period. All values are in percent. The table is arranged in alphabetical order by the funds' name. The bottom row shows the average alpha and differential return.

	α	r_i - $OSEFX$
Alfred Berg	2.51%	3.51%
Danske Bank	2.92%	2.62%
DNB	-0.53%	-0.66%
Eika	-0.39%	-1.09%
KLP	0.75%	0.37%
Nordea	0.90%	0.78%
ODIN	-1.16%	-2.65%
Pareto	1.31%	0.09%
Storebrand	1.35%	1.51%
Average	0.85%	0.50%

6.3 Periods of High Market Fear

Next, we will delve more into the scenario of managing mutual funds in a volatile market. As previously shown, identified times can be described as temporal leaps with substantial market fear, which will be investigated closer. Our findings present actual operations in mutual funds during a volatile market. Each period in the following sections represents the defined periods introduced in section 4.3. See appendix A2 for calculations with Single-factor model.

6.3.1 R-squared and Tracking Error

Table 6.5: Extracted Periods R-squared and Tracking Error

The table below shows the mutual funds' R-squared and tracking error value. The table has four panels: Each panel represents the values throughout our four periods (1, 2, 3, and 4). All values are in percent. The panels are arranged in alphabetical order by the funds' name. The bottom row of each panel provides the average R^2 and tracking error value.

Period 1	**Ex-ante**		**Event**		**Ex-post**	
	R^2	**TE**	**R^2**	**TE**	**R^2**	**TE**
Alfred Berg	89.4%	11.77%	94.0%	21.16%	92.7%	8.98%
Danske Bank	93.6%	10.68%	96.6%	21.29%	94.0%	8.83%
DNB	97.7%	5.30%	98.3%	9.58%	98.5%	3.78%
Eika	93.2%	10.18%	97.7%	12.36%	95.0%	7.56%
KLP	97.1%	6.88%	96.7%	13.57%	98.0%	4.91%
Nordea	98.3%	4.59%	99.6%	5.36%	99.4%	3.16%
ODIN	80.6%	18.67%	70.7%	43.56%	70.0%	18.37%
Pareto	89.8%	12.47%	91.1%	25.84%	86.7%	12.56%
Storebrand	98.4%	4.34%	99.4%	5.32%	99.4%	2.62%
Average	93.1%	9.43%	93.8%	17.56%	92.6%	7.86%

Period 2	**Ex-ante**		**Event**		**Ex-post**	
	R^2	**TE**	**R^2**	**TE**	**R^2**	**TE**
Alfred Berg	88.6%	7.04%	96.9%	9.27%	91.3%	8.11%
Danske Bank	92.6%	5.64%	98.3%	8.02%	95.2%	6.39%
DNB	98.4%	2.51%	99.6%	5.10%	98.8%	2.95%
Eika	95.0%	4.73%	98.5%	6.04%	98.3%	4.43%
KLP	96.2%	3.97%	99.1%	5.63%	98.0%	4.12%
Nordea	98.3%	2.93%	99.1%	5.01%	97.4%	4.50%
ODIN	65.2%	11.74%	88.0%	19.92%	76.9%	13.74%
Pareto	82.7%	8.35%	94.3%	13.34%	85.0%	10.65%
Storebrand	99.1%	1.98%	99.8%	2.30%	99.2%	2.45%
Average	90.7%	5.43%	97.1%	8.29%	93.4%	6.37%

Period 3	**Ex-ante**		**Event**		**Ex-post**	
	R^2	**TE**	**R^2**	**TE**	**R^2**	**TE**
Alfred Berg	86.6%	8.11%	96.2%	9.71%	95.5%	8.77%
Danske Bank	93.7%	5.74%	94.2%	11.28%	94.7%	9.58%
DNB	99.0%	2.06%	99.5%	4.05%	99.6%	3.33%
Eika	94.4%	5.08%	92.9%	12.71%	97.9%	6.67%
KLP	97.9%	3.13%	98.8%	5.54%	98.5%	5.25%
Nordea	98.6%	2.70%	99.2%	4.42%	98.9%	4.39%
ODIN	71.0%	11.78%	81.9%	20.91%	78.3%	18.31%
Pareto	90.3%	6.86%	93.1%	13.17%	94.5%	10.80%
Storebrand	98.7%	2.44%	99.6%	2.97%	99.6%	2.92%
Average	92.3%	5.32%	95.0%	9.42%	95.3%	7.78%

Period 4	**Ex-ante**		**Event**		**Ex-post**	
	R^2	**TE**	**R^2**	**TE**	**R^2**	**TE**
Alfred Berg	85.6%	7.65%	98.1%	11.70%	89.6%	9.62%
Danske Bank	87.7%	6.73%	95.3%	14.06%	89.3%	8.42%
DNB	97.2%	3.25%	98.8%	7.99%	97.7%	4.35%
Eika	96.5%	3.65%	98.7%	9.26%	95.5%	6.06%
KLP	96.2%	3.88%	98.6%	7.55%	96.6%	4.61%
Nordea	94.5%	5.56%	95.9%	18.56%	91.6%	7.66%
ODIN	93.6%	4.23%	97.8%	9.37%	96.4%	5.31%
Pareto	92.0%	5.08%	97.3%	14.04%	93.6%	8.71%
Storebrand	96.5%	3.97%	98.3%	7.38%	97.1%	4.89%
Average	93.3%	4.89%	97.7%	11.10%	94.2%	6.63%

To observe a change in management, we have calculated estimates for all three periods ex-ante, event, and ex-post. We see an average change in every period where mutual funds increase their R^2 from ex-ante to the event. Findings present ODIN to become more actively managed in Period 1. In Period 3, Eika adjusts its portfolio to accomplish a decrease of 1.5% in R^2. Average R^2 then decreases from event to ex-post for three of the periods. Period 3 is the only period to experience a stable R^2 in ex-post where we identify an increase by 0.3%.

It is important to emphasize that ex-ante and ex-post might have higher VIX values than periods not classified and included. In Table 6.5, we do not have information to define if there has been a change in R^2 in front of ex-ante. Due to rising VIX values in ex-ante, mutual fund managers may have reconstructed the portfolio in advance. Nevertheless, Table 6.5 visualizes an average R^2 to be highest within the event for each period. We see consistency in mutual funds, which have a high R^2 in ex-ante to be exposed between 98-100% in the event for each period. Storebrand and DNB report to have a high R^2 in the event for every period. The lowest measurement of R^2 presented for these mutual funds is 98.3%. The similarity is found for Nordea and KLP, where they have R^2 values in the event between the same low intervals. However, both reports of lower R^2 in one period each. KLP has an R^2 of 96.7% in Period 1, while Nordea has an R^2 of 95.9% in Period 4.

Period 3 is the only period to increase average R^2 values from event to ex-post. This period also experiences the least change of TE after an event period. Based on TE measures, we see ODIN has the highest values for all periods without Period 4, where they no longer have the lowest R^2 value. The highest average TE measures are found in Period 1, where we consistently can see the lowest average R^2 values. Period 4 presents the second largest TE values. Periods 1 and 4 can commonly be characterized as crises and reflect the highest TE values. For the two periods affected by market fear but not characterized as crises, we have TE measures to be between 8-10%. An interesting finding can be expressed in Period 4, where we see an average R^2 to be higher than Period 2 and 3 and representing higher TE measures.

Generally, we can see the lowest average R-squared reported in Period 1, while the highest average R^2 is found in Period 4. Therefore, these two periods represent the highest and lowest measured active management but still reflect the highest TE in both periods. More precisely, we can see that the most actively managed individual mutual fund based on R^2 represents the highest measures of TE in Period 1-3. However, in Period 4, the most active mutual fund does not represent the highest TE.

6.3.2 Alpha and Differential Return

Table 6.6: Extracted Periods Alpha and Differential Return

The table below shows the mutual funds' annualized alpha and differential return. The table has four panels: Each panel represents the values throughout our four periods (1, 2, 3, and 4). All values are in percent. The panels are arranged in alphabetical order by the funds' name. The bottom row of each panel presents the average alpha and differential return.

Period 1	**Ex-ante**		**Event**		**Ex-post**	
	α	r_i - OSEFX	α	r_i - OSEFX	α	r_i - OSEFX
Alfred Berg	-7.71%	-7.48%	-9.51%	4.98%	8.51%	1.39%
Danske Bank	-23.41%	-13.59%	4.17%	22.64%	21.86%	10.81%
DNB	5.23%	5.48%	14.23%	17.76%	4.47%	-0.21%
Eika	-11.63%	-2.78%	14.43%	20.15%	11.38%	7.75%
KLP	-2.95%	3.18%	7.40%	10.60%	10.31%	7.07%
Nordea	-5.92%	-2.95%	5.66%	9.12%	6.53%	3.35%
ODIN	-20.38%	0.68%	-20.59%	11.82%	5.83%	-13.43%
Pareto	-3.25%	7.10%	12.35%	29.76%	11.13%	-2.89%
Storebrand	-1.26%	0.05%	5.58%	7.34%	3.36%	1.58%
Average	-7.92%	-1.14%	3.75%	14.91%	9.26%	1.71%

Period 2	**Ex-ante**		**Event**		**Ex-post**	
	α	r_i - OSEFX	α	r_i - OSEFX	α	r_i - OSEFX
Alfred Berg	0.85%	-4.40%	-16.67%	-18.06%	4.66%	-9.02%
Danske Bank	-1.62%	-1.64%	22.00%	19.26%	-12.05%	-22.16%
DNB	0.91%	0.10%	2.53%	13.61%	-9.70%	-12.12%
Eika	1.34%	-1.80%	-12.72%	-17.92%	-9.23%	-17.30%
KLP	5.94%	4.53%	2.42%	1.65%	-15.65%	-21.88%
Nordea	4.33%	2.77%	-5.69%	1.55%	-5.10%	-10.63%
ODIN	37.00%	34.07%	22.01%	-9.04%	-19.51%	-46.03%
Pareto	10.38%	5.41%	-7.61%	-0.52%	7.39%	-9.88%
Storebrand	3.77%	3.17%	-10.48%	-8.32%	6.05%	3.08%
Average	6.99%	4.69%	-0.47%	-1.98%	-5.91%	-16.22%

Period 3	**Ex-ante**		**Event**		**Ex-post**	
	α	r_i - OSEFX	α	r_i - OSEFX	α	r_i - OSEFX
Alfred Berg	-41.07%	-18.51%	-32.19%	-21.39%	8.66%	7.77%
Danske Bank	-13.93%	2.32%	13.01%	18.17%	26.16%	24.65%
DNB	6.19%	6.41%	10.70%	13.83%	1.70%	2.26%
Eika	-21.50%	-15.98%	-34.20%	-27.80%	-7.05%	-12.77%
KLP	3.28%	2.40%	-4.85%	-4.11%	-0.16%	-3.74%
Nordea	-6.12%	0.08%	1.00%	2.98%	-0.21%	-0.37%
ODIN	-42.41%	-20.10%	-55.38%	-48.45%	16.49%	-0.14%
Pareto	-7.50%	4.06%	-17.41%	-15.47%	-2.53%	-5.31%
Storebrand	-1.92%	-1.08%	-0.77%	0.96%	-3.72%	-2.96%
Average	-13.89%	-4.49%	-13.34%	-9.03%	4.37%	1.04%

Period 4	**Ex-ante**		**Event**		**Ex-post**	
	α	r_i - OSEFX	α	r_i - OSEFX	α	r_i - OSEFX
Alfred Berg	23.97%	30.12%	-5.26%	7.20%	23.59%	16.28%
Danske Bank	16.10%	23.10%	0.64%	1.29%	22.86%	25.10%
DNB	-15.36%	-15.81%	13.72%	-4.31%	-6.55%	-2.52%
Eika	-1.26%	-3.75%	-19.50%	6.09%	-7.29%	-14.23%
KLP	-8.88%	-13.75%	5.31%	-3.94%	9.12%	8.77%
Nordea	2.11%	-2.04%	-15.53%	-17.27%	16.62%	14.91%
ODIN	5.02%	6.35%	-1.29%	-13.55%	0.34%	-0.11%
Pareto	6.91%	2.15%	1.82%	-26.44%	-10.79%	-6.12%
Storebrand	6.58%	5.51%	-7.50%	1.42%	5.37%	12.18%
Average	3.91%	3.54%	-3.07%	-5.50%	5.92%	6.03%

Return not explained by the model will be presented in the mutual fund's alpha. We find that the mutual funds have negative average alpha within the event for three periods. We can interpret findings as estimates of benchmark outperforming the actively managed mutual fund in three of our periods of high market fear. As we can see, the mutual funds have a positive alpha and outperform the benchmark.

In Table 6.6, we see an average differential return to decrease from ex-ante to event within three periods. Looking at the event periods, Period 1 is the only one with a positive average alpha and differential return. On the other hand, findings in ex-post show three periods with a positive average alpha and differential return.

The table presents findings where alpha and differential return can simultaneously represent positive and negative values. For example, Alfred Berg has a differential return of 7.2%, while their risk-adjusted return is -5.26% within the event of Period 4. We find the highest positive average alpha in ex-post Period 1. As presented in Table 6.5, this period is one of the most actively managed. For Period 4, we see the second most prominent average differential return. As shown in Table 6.1, this is the period with the highest average ex-post VIX values.

6.4 Inspecting Factor Composition for Period 1 and 3

Further, we want to analyze two of our periods in-depth. This section will focus on Period 1 and Period 3 to understand their factor exposure from ex-ante to event in order to suggest changes in R^2 and alpha. These periods are selected to visualize the mutual funds adjusting their portfolio to be more actively managed.

Table 6.7: Period 1 FFC Output

The table shows the mutual funds' R-squared, annualized alpha, and risk factor coefficients. The alpha and R-squared values are in percent. The table has two panels: one shows the values throughout ex-ante, and the other displays the values throughout the event period. These two periods are extracted from Period 1. The panels are ranked by the funds' R-squared, from lowest to highest R^2 value. The bottom row in each panel provides the average R^2, alpha and beta coefficients. T-statistics are shown in parenthesis. Significance levels *p <0.1; **p <0.05; ***p <0.01.

Ex-ante	$\mathbf{R}^2$	α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}
ODIN	80.6%	-20.38%*	0.66***	0.27***	0.10**	-0.08
		(-1.69)	(20.25)	(5.53)	(2.20)	(-1.34)
Alfred Berg	89.4%	-7.71%	1.01***	0.28***	-0.03	0.03
		(-0.54)	(26.34)	(4.87)	(-0.55)	(0.38)
Pareto	89.8%	-3.25%	0.82***	0.20***	-0.03	-0.02
		(-0.29)	(26.56)	(4.48)	(-0.68)	(-0.31)
Eika	93.2%	-11.63%	0.85***	0.14***	-0.01	-0.12**
		(-1.19)	(32.12)	(3.50)	(-0.31)	(-2.51)
Danske Bank	93.6%	-23.41%**	0.79***	0.14***	-0.12***	-0.02
		(-2.57)	(32.31)	(3.87)	(-3.48)	(-0.44)
KLP	97.1%	-2.95%	0.89***	0.08***	-0.00	-0.03
		(-0.44)	(48.87)	(2.89)	(-0.03)	(-0.94)
DNB	97.7%	5.23%	0.97***	0.00	-0.07***	0.05
		(0.75)	(51.83)	(0.14)	(-2.71)	(1.46)
Nordea	98.3%	-5.92%	0.94***	0.01	-0.01	0.02
		(-1.04)	(61.37)	(0.35)	(-0.63)	(0.57)
Storebrand	98.4%	-1.26%	0.96***	0.01	-0.05**	-0.00
		(-0.22)	(62.78)	(0.42)	(-2.37)	(0.01)
Average	93.1%	-7.92%	0.88	0.13	-0.02	-0.02

Event	$\mathbf{R}^2$	α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}
ODIN	70.6%	-20.59%	0.49***	0.23***	0.00	-0.21***
		(-0.76)	(11.94)	(3.89)	(0.01)	(-2.92)
Pareto	91.1%	12.35%	0.72***	0.10**	0.00	-0.08
		(0.61)	(23.53)	(2.37)	(0.07)	(-1.48)
Alfred Berg	94.0%	-9.51%	0.78***	0.08**	-0.09**	-0.01
		(-0.53)	(28.63)	(2.01)	(-1.99)	(-0.12)
Danske Bank	96.6%	4.17%	0.73***	0.09***	-0.11***	-0.04
		(0.33)	(38.27)	(3.18)	(-3.40)	(-1.21)
KLP	96.7%	7.40%	0.94***	0.10***	0.00	-0.04
		(0.48)	(40.13)	(3.05)	(0.03)	(-1.09)
Eika	97.7%	14.43%	0.91***	0.08***	-0.02	-0.04
		(1.15)	(47.41)	(2.92)	(-0.74)	(-1.15)
DNB	98.3%	14.23%	0.95***	-0.07***	-0.05	0.09***
		(1.18)	(51.79)	(-2.67)	(-1.59)	(2.73)
Storebrand	99.4%	5.58%	0.97***	0.01	-0.01	-0.00
		(0.81)	(92.87)	(0.65)	(-0.79)	(-0.19)
Nordea	99.6%	5.66%	0.95***	0.02	-0.00	-0.02
		(1.04)	(115.28)	(1.50)	(-0.13)	(-1.59)
Average	93.8%	3.75%	0.83	0.07	-0.03	-0.04

ODIN has the lowest R^2 throughout both periods. This is the only fund that increases the degree of active management from ex-ante to event. Parallelly their alpha becomes more negative, but no longer statistically significant at a 10% level. Danske Bank has the most negative and statistically significant alpha in ex-ante. For the event, the alpha becomes positive. However, the statistical significance disappears. It is also the most remarkable change in alpha between ex-ante and event for all mutual funds. Danske Bank reduced the degree of active management and their exposure to the market coefficient. Table 6.7 also indicates Danske Bank to have a portfolio less exposed to small-capitalization and growth stocks in the event. The factor coefficients are statistically significant within the 1% significance level in both periods.

DNB goes from no weight in the SMB portfolio to being exposed toward big-capitalization stocks and reducing its exposure to growth stocks in the event. Focusing on the HML coefficient in Table 6.7, we see it is no longer significant in event. Moreover, DNB is the only fund with positive alpha in ex-ante, while Eika has the highest positive alpha in event. Eika has reduced exposure toward small-capitalization stocks in event and increased its exposure to the market volatility coefficient. All funds have a statistically significant market coefficient within the 1% significance level in both periods. Alfred Berg, the only fund with higher market volatility than the benchmark OSEFX in ex-ante, has a lower market coefficient than average in the event. The fund is, together with ODIN, the only one with negative alpha in event.

Average alpha goes from being negative in ex-ante to positive in the event. The average R^2 has a minor increase from ex-ante to event. Median R^2 increases by more than 3%. After entering the event average market coefficient and SMB coefficient decrease, while the HML and PR1YR coefficients become more negative.

Table 6.8: Period 3 FFC Output

The table shows the mutual funds' R-squared, annualized alpha, and risk factor coefficients. The alpha and R-squared values are in percent. The table has two panels: one shows the values throughout ex-ante, and the other displays the values throughout the event period. These two periods are extracted from Period 3. The panels are ranked by the funds' R-squared, from lowest to highest R^2 value. The bottom row in each panel provides the average R^2, alpha and beta coefficients. T-statistics are shown in parenthesis. Significance levels *p <0.1; **p <0.05; ***p <0.01.

Ex-ante	R^2	α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}
ODIN	71.0%	-42.41%**	0.78***	0.22*	0.15*	-0.02
		(-1.98)	(8.18)	(1.87)	(1.72)	(-0.11)
Alfred Berg	86.6%	-41.07%**	0.74***	0.02	-0.02	0.25**
		(-2.48)	(10.10)	(0.28)	(-0.29)	(2.39)
Pareto	90.3%	-7.50%	0.81***	0.03	-0.03	0.00
		(-0.55)	(13.43)	(0.43)	(-0.53)	(0.02)
Danske Bank	93.7%	-13.93%	0.84***	0.04	-0.01	0.21***
		(-1.17)	(15.90)	(0.65)	(-0.28)	(2.85)
Eika	94.4%	-21.50%*	1.01***	0.11*	0.07	0.05
		(-1.80)	(19.01)	(1.72)	(1.49)	(0.63)
KLP	97.9%	3.28%	1.02***	0.05	0.03	-0.05
		(0.44)	(30.94)	(1.29)	(0.90)	(-1.02)
Nordea	98.6%	-6.12%	0.98***	0.06*	0.04	0.08**
		(-1.02)	(36.69)	(1.76)	(1.53)	(2.17)
Storebrand	98.7%	-1.92%	1.02***	0.04	0.01	0.02
		(-0.32)	(38.14)	(1.23)	(0.59)	(0.46)
DNB	99.0%	6.19%	0.98***	-0.01	-0.01	-0.00
		(1.21)	(43.40)	(-0.50)	(-0.56)	(-0.15)
Average	92.2%	-13.89%	0.91	0.06	0.03	0.06

Event	R^2	α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}
ODIN	81.9%	-55.38%	0.89***	0.25*	0.16	-0.04
		(-1.47)	(8.74)	(1.85)	(0.98)	(-0.33)
Eika	92.9%	-34.20%	0.95***	-0.03	-0.02	-0.15*
		(-1.19)	(12.18)	(-0.25)	(-0.19)	(-1.70)
Pareto	93.1%	-17.41%	0.95***	0.08	0.20*	-0.10
		(-0.68)	(13.65)	(0.88)	(1.80)	(-1.21)
Danske Bank	94.2%	13.01%	0.93***	0.03	0.02	-0.04
		(0.53)	(13.93)	(0.38)	(0.17)	(-0.57)
Alfred Berg	96.2%	-32.19%	0.89***	-0.04	-0.09	-0.10
		(-1.60)	(16.32)	(-0.57)	(-1.06)	(-1.58)
KLP	98.8%	-4.85%	0.97***	0.03	0.07	-0.01
		(-0.43)	(31.55)	(0.74)	(1.47)	(-0.39)
Nordea	99.2%	1.00%	0.96***	-0.03	0.02	0.01
		(0.10)	(35.77)	(-0.79)	(0.59)	(0.23)
DNB	99.4%	10.70%	0.94***	-0.01	0.00	0.03
		(1.37)	(44.47)	(-0.21)	(0.15)	(1.36)
Storebrand	99.6%	-0.77%	0.98***	0.02	-0.02	0.02
		(-0.12)	(56.38)	(0.83)	(-0.73)	(0.86)
Average	95.0%	-13.34%	0.94	0.03	0.04	-0.04

Eika is the only fund that increases the degree of active management from ex-ante to event. The fund's alpha becomes more negative between the periods. However, the significant level disappears. Danske Bank has the most major change from negative to positive alpha values between ex-ante and event. The alpha values in the event are no longer significant. The fund increases R-squared and exposure to market coefficient.

The return on Danske Bank is positively correlated with the one-year momentum factor, which also applies to Alfred Berg and Nordea. These funds are the only funds with a higher PR1YR coefficient than the average in ex-ante. Jointly these funds present negative alpha, which indicates that exposure to momentum may give a negative alpha. These funds have a non-significant PR1YR coefficient close to zero in the event.

ODIN has the most negative alpha in both periods. Corresponding to Eika, their alpha becomes more negative in events with no significance. ODIN is the fund with the highest degree of active management in both periods, even though active management is reduced by more than 10% from ex-ante to event. DNB has the highest R^2 and most positive alpha in ex-ante. Only DNB and KLP have a positive alpha in this period. These funds have a market coefficient close to the benchmark and reduce their degree of active management and market coefficient in event.

Nevertheless, DNB achieves a positive alpha while KLP achieves a negative alpha. By inspecting their HML coefficients, KLP increases its exposure to value stocks between the periods.

6.5 Management and Performance Against Passive Investment Opportunities

Through our research, we have focused management and performance of mutual funds against OSEFX as the benchmark. All funds included in the analysis utilize this index as their reference. Mutual funds determine their benchmark by themselves, which indicates that they can compare themselves to convenient self-interest references that can shed light on better performance.

Table 6.9: Passive Benchmarks

The table below shows the mutual funds' R-squared and annualized alpha using different benchmarks: OSEFX, Alfred Berg Index and KLP Index. OSEFX is our standard benchmark. The table has four panels: Each panel represents the values throughout the event period in our four periods (1, 2, 3, and 4). All values are in percent. The panels are arranged in alphabetical order by the funds' name. The bottom row in each panel presents the average alpha and R-squared value.

Period 1	**OSEFX**		**Alfred Berg Index**		**KLP Index**	
	R^2	α	R^2	α	R^2	α
Alfred Berg	94.0%	-9.51%	89.6%	-21.09%	90.9%	-18.88%
Danske Bank	96.6%	4.17%	94.2%	-5.06%	95.0%	-3.37%
DNB	98.3%	14.23%	98.8%	5.52%	99.8%	8.12%
Eika	97.7%	14.43%	95.0%	2.86%	95.6%	4.68%
KLP	96.7%	7.40%	93.3%	-5.24%	94.0%	-3.28%
Nordea	99.6%	5.66%	97.1%	-6.44%	98.0%	-4.04%
ODIN	70.7%	-20.59%	65.6%	-28.89%	66.2%	-27.81%
Pareto	91.1%	12.35%	89.1%	3.65%	91.2%	6.42%
Storebrand	99.4%	5.58%	96.7%	-7.06%	97.8%	-4.39%
Average	93.8%	3.75%	91.0%	-6.86%	92.1%	-4.73%

Period 2	**OSEFX**		**Alfred Berg Index**		**KLP Index**	
	R^2	α	R^2	α	R^2	α
Alfred Berg	96.9%	-16.67%	96.1%	-24.61%	96.2%	-22.98%
Danske Bank	98.3%	22.00%	98.0%	14.72%	97.9%	16.07%
DNB	99.6%	2.53%	99.9%	-3.25%	99.9%	-1.90%
Eika	98.5%	-12.72%	98.0%	-20.53%	98.0%	-19.06%
KLP	99.1%	2.42%	98.7%	-5.01%	98.7%	-3.52%
Nordea	99.1%	-5.69%	98.8%	-12.63%	98.8%	-11.25%
ODIN	88.0%	22.01%	86.6%	13.60%	86.5%	14.88%
Pareto	94.3%	-7.61%	94.0%	-13.77%	94.0%	-12.51%
Storebrand	99.8%	-10.48%	99.6%	-17.76%	99.6%	-16.17%
Average	97.1%	-0.47%	96.6%	-7.69%	96.6%	-6.27%

Period 3	**OSEFX**		**Alfred Berg Index**		**KLP Index**	
	R^2	α	R^2	α	R^2	α
Alfred Berg	96.2%	-32.19%	95.4%	-45.81%	95.2%	-47.45%
Danske Bank	94.2%	13.01%	94.2%	-0.46%	94.1%	-2.11%
DNB	99.5%	10.70%	99.9%	-2.40%	99.9%	-3.97%
Eika	92.9%	-34.20%	91.9%	-49.02%	91.9%	-50.61%
KLP	98.8%	-4.85%	98.7%	-18.97%	98.7%	-20.60%
Nordea	99.2%	1.00%	98.9%	-13.08%	98.7%	-14.81%
ODIN	81.9%	-55.38%	81.0%	-68.94%	81.2%	-70.27%
Pareto	93.1%	-17.41%	92.4%	-31.71%	92.4%	-33.30%
Storebrand	99.6%	-0.77%	99.2%	-15.32%	99.1%	-17.07%
Average	95.0%	-13.34%	94.6%	-27.30%	94.6%	-28.91%

Period 4	**OSEFX**		**Alfred Berg Index**		**KLP Index**	
	R^2	α	R^2	α	R^2	α
Alfred Berg	98.1%	-5.26%	97.0%	-4.37%	97.2%	-6.18%
Danske Bank	95.3%	0.64%	95.1%	1.53%	95.5%	-0.25%
DNB	98.8%	13.72%	98.5%	14.61%	98.5%	12.83%
Eika	98.7%	-19.50%	98.5%	-18.74%	98.6%	-20.26%
KLP	98.6%	5.31%	98.5%	6.19%	98.6%	4.43%
Nordea	95.9%	-15.53%	96.0%	-14.61%	96.1%	-16.45%
ODIN	97.8%	-1.29%	97.6%	-0.46%	97.4%	-2.13%
Pareto	97.3%	1.82%	97.6%	2.74%	97.3%	0.90%
Storebrand	98.3%	-7.50%	97.9%	-6.67%	98.0%	-8.35%
Average	97.7%	-3.07%	97.4%	-2.19%	97.5%	-3.94%

Table 6.9 has chosen to include two passively managed funds as a benchmark. These funds are selected for their existence throughout the whole time-period and are the substitutes for the same type of mutual fund with passive management. Both passively managed funds have the same distributor represented in the population and can be viewed as an alternative investment.

Interesting findings are proposed in their R^2 and alpha, where the table visualizes that management is more explained by OSEFX. When comparing the same mutual funds against passive alternatives, it occurs lower R^2 values which indicate greater portfolio deviation. The fact that we can infer a more remarkable divergence in alpha due to differences in benchmark between active and passive opportunities is an intriguing discovery.

Utilizing passive managed mutual funds as a reference instead of OSEFX makes the actual return lower. Investors will see active fund distributors marketing with greater abnormal returns. However, the return from active management must be adjusted for fees. Consequently, active management may give a lower actual return than passive.

6.6 Testing for Statistical Significance

We will run Z-tests to check if changes in alpha and R^2 are statistically significant. Since the Z-test is a type of hypothesis test, we need to make hypotheses to run the test.

H_0*: There is no significant difference between the specified populations*

H_1*: There is a significant difference between the specified populations*

If the p-value is less than the significance level, H_0 will be rejected, and we will accept the alternative hypothesis. If the p-value does not qualify to be statistically significant, we cannot reject H_0.

Table 6.10: P-values Output from Z-test

The table below shows the corresponding p-values from the z-statistics (see appendix A3) for a two-tailed Z-test for the mutual funds. The table has two panels: one displays the p-values for the Z-test on the mutual funds annualized alpha, and the other represents the p-values for the Z-test on the mutual funds' R-squared. The panels have four columns. Each column shows the p-values throughout the event period in our four periods (1, 2, 3, and 4). The panels are arranged in alphabetical order by the funds' name. Significance levels *p <0.1; **p <0.05; ***p <0.01.

P-values output from alpha Z-test

	Period 1	Period 2	Period 3	Period 4
Alfred Berg	0.000***	0.000***	0.000***	0.021**
Danske Bank	0.495	0.000***	0.001***	0.476
DNB	0.000***	0.461	0.002***	0.000***
Eika	0.000***	0.001***	0.000***	0.000***
KLP	0.001***	0.670	0.095*	0.192
Nordea	0.020**	0.097	0.976	0.000***
ODIN	0.000***	0.000***	0.000***	0.961
Pareto	0.000***	0.011**	0.000***	0.872
Storebrand	0.058*	0.007***	0.569	0.023**

P-values output from R-squared Z-test

	Period 1	Period 2	Period 3	Period 4
Alfred Berg	0.022**	0.048**	0.039**	0.010**
Danske Bank	0.000***	0.014**	0.123	0.068*
DNB	0.724	0.619	0.584	0.721
Eika	0.054*	0.226	0.719	0.164
KLP	0.968	0.563	0.552	0.613
Nordea	0.075*	0.437	0.354	0.982
ODIN	0.000***	0.000***	0.045**	0.000***
Pareto	0.011**	0.028**	0.028**	0.001***
Storebrand	0.000***	0.001***	0.000***	0.001***

There are most significant changes in the funds' alpha. Alfred Berg is the only fund with statistically significant changes in alpha and R^2 for all periods. Significant changes are identified within a 1% level for alpha in Periods 1-3, and a 5% level for alpha in Period 4 and R^2 in all periods. Eika has statistically significant changes in alpha within a 1% level in all periods, which means that we reject H_0 and accept H_1 that the changes are not due to coincidences. Storebrand has statistically significant R^2 changes within a significance level of 1% in all periods. As presented in Table 6.5, their R^2 is close to 1 in all event periods. This may indicate that Storebrand has a conscious strategy in periods of high market fear. They also have a significant change in alpha in three event periods.

6.7 Robustness

In order to retrieve an effective and unbiased analysis, securing the robustness of the analysis is essential with correctly applied models. This chapter will ensure the robustness of our research and estimates.

Dataset

Our dataset consists of 9 different Norwegian mutual funds, representing a small share of mutual funds in Norway today. A smaller sample size will negatively impact the statistical force (Fornell et al., 2009). Increasing sample size might enhance the statistical power of the analysis. The dataset consists of NAV's which differ in size and value. Therefore, we convert the mutual funds' NAV to logarithmic returns to make changes comparable.

Time-period

For our calculated market fear periods, the length of time interval differs. We do not have a determined time leap for how long we analyze the periods and consistently use them. For example, Period 1 defines a period of two years divided into ex-ante, event, and ex-post equally. The estimates for recovery and performance after a period of high market fear are longer than the recovery period after high VIX in Period 4, which lasted over seven months. However, it will bring more statistical power to equally examine the length of ex-ante, event, and ex-post in all periods.

Observations and estimates

All 42,545 observations on mutual funds, VIX, and OSEFX are based on daily observations. These observations vary in different trading days, resulting in missing values. To minimize bias in our sample, we omit variables with value NA. In practice, our regression will focus on trading days where all variables have observations. If one or more variables are not observed, we omit the trading day. This method suppresses the problem of bias.

7 Discussion of Findings

Furthermore, we want to discuss the most valuable findings more accurately. Therefore, our focus will be on actual discoveries and what we can expect from mutual funds in future cases.

7.1 Main Question

Earlier in the thesis, we addressed our research questions where we enlightened our main question:

Do active mutual funds become more actively managed in periods of high market fear?

We see changes in the degree of active management for all funds in each period. This indicates that high market fear has an impact on active management. By interpreting the findings measured by R^2, only two mutual funds seem to increase the degree of active management when the market fear is high. One of the funds is ODIN in Period 1, and the second is Eika in Period 3. From Table 6.5, we can expect R^2 to increase in periods of high market fear. Calculations of R^2 indicate an increase from ex-ante to event in 94.4%[10] of the cases. Therefore, our findings cannot argue for actively managed mutual funds becoming more actively managed in periods affected by market fear.

One may ask why actively managed funds reduce the degree of active management during periods of high market fear. Crises are times of stock market anomalies, in other words, opportunities for active management to profit from market inefficiencies (Brunnermeier & Oehmke, 2013). Therefore, we should expect the funds' managers to increase the degree of active management.

[10] 9 mutual funds x 4 periods = 36 R-squared values. $[\frac{(36-2)}{36}] = 94.44\%$.

According to Osborne and Clarke (2020), investors are seeking liquidity and index-tracking funds during recessions as revenues dry up and unemployment increases. Fund managers can thus reduce active management to avoid big losses. The managers may have restrictions for how to invest in times of market anomalies, which can involve a lower degree of active management. According to portfolio manager Vogt (2021), a higher R^2 in times of crisis does not necessarily mean that managers reduce active management. It may increase because the exposure to factors in the Carhart model explains more of the variation in the funds' return due to higher market volatility. This suggests that using R^2 as a measure of active management in periods of market anomalies may be misleading. Unfortunately, we do not have insight into the funds' portfolios, so we cannot determine what causes the changes in the degree of active management in periods of high market fear.

Since TE estimates may explain the difference in the portfolio variance between the mutual funds and the benchmark, we expect high TE to indicate significant differences between the portfolios. For event, where mutual funds generally decrease their degree of active management based on R^2 we can in contrast see an increase in TE. Since we are experiencing higher TE when R^2 indicates a lower degree of active management, we must consider the environmental affection. In the event, volatility levels are abnormally high, directly affecting TE. A variance between a mutual fund and benchmark returns is amplified by the environment exposed for volatility. A higher R^2 indicates that a smaller share of the variation is due to tracking error, and more is due to the indices the fund mimics (Amihud & Goyenko, 2013). The discrepancies will be significantly amplified differently because of volatility, which generates higher TE, although the portfolios represent more passively managed mutual funds.

Investment strategy

It is crucial to consider the investment mandates mutual funds are restricted to. A mutual fund often has a long-term investment horizon and focuses on accumulating returns in the long run. They are not behaving as traders, which might explain why they do not readjust their portfolios frequently (Øvrebø, 2021). The investment mandates can concretize how much to invest in the market and the volume of cash balance. Some might be forced to hold positions in the market and minimize cash holdings. A reduced risk adjustment can adapt the portfolio to a more index-concentrated portfolio where the exposure is focused on the market itself. This results in a portfolio that will accomplish equal and parallel returns with the market. Another effect of this risk adjustment is limiting losses to what the market generally loses. Alternatively, focus the portfolio more away from the market to generate an abnormal return by good stock picking. If the mandates indicate the fund can hold a more significant cash balance, they are freer to sell positions in advance of high VIX. This might limit losses and generate cash reserves for good stock picking when the market possibly reflects underpriced stocks.

We can see from a newly published interview with different portfolio managers in Norway, that portfolio managers account for market fear in their investment strategy (Nilsen, 2021). This interview also implicitly states that market fear is assessed by portfolio managers and assists in the process of future management of the portfolio. Either by having a portfolio concentrated at benchmark or trying to exploit stock-picking opportunities while other investors are uncertain. To conclude, mutual funds have different investment mandates, and findings may indicate hollowing volatility parity strategies.

7.2 Additional Research Questions

By utilizing our findings, we want to investigate the performance results from the changes in active management made in periods of high VIX.

7.2.1 Does a higher degree of active management indicate better performance?

Although professional investors should stand in a position to be more skilled in choosing great stocks generating abnormal returns, we find that it is not necessarily the case for most mutual funds.

To fulfill abnormal return and outperformance, literature brings active management as a condition. From the regressions with the four-factor model, we can understand the movement and decisions within a mutual fund to comply with a lower degree of active management in turbulent markets. The represented mutual funds in our dataset generally lower their degree of active management in events when the environment is strongly affected by fear. The outcome is a portfolio more similar to the benchmark, which results in performance behaving more accordingly.

The performance of a mutual fund springs from decisions and trades done by portfolio managers. It is important to mention that the mutual fund population represents a wide range of Norwegian mutual funds in the same investment universe. Still, they most likely have different investment strategies. These strategies and investment mandates restrict all the funds to boundaries that might affect the performance. A mutual fund can sell parts of its portfolio to increase cash balance and pick stocks for different instances.

Nevertheless, we can see higher alpha values for the mutual funds implementing an increased level of active management. The increased alpha values occur because an investment strategy deviates from the benchmark. This strategy does not necessarily indicate better performance. Better performance over time is a result of the combination of active management and skill. Divergence in a greater scale caused by active management could also initiate a negative alpha. Therefore, active management is insufficient to accomplish outstanding performance, but it is a necessary condition.

7.2.2 Do professional investors increase performance after periods of high market fear?

Indications from the ex-post sections show that a higher level of active management changes the alpha more drastically. These alpha values can both be substantially positive or negative.

Implicit states that it is possible to do great stock picking in periods of high market fear and exploit opportunities that bring an excess return in ex-post. However, it is also possible to achieve drastic negative changes in alpha. The foundation of spread in alpha is the portfolio manager's ability to pick good stocks rather than inadequately quality decisions. However, we can see mutual funds having positive average alpha and outperforming the benchmark in ex-post for three periods. Table 6.6 depicts that mutual funds becoming more similar to the benchmark have steadier performance in the form of alpha. These mutual funds can often accomplish deviating alpha caused by some degree of active management. However, one crucial reminder of the performance for these closet-index funds is the perspective of charging a fee for their active management. Consequently, a mutual fund with a positive alpha does not implicitly indicate good performance. The fund itself can beat the benchmark, but it might not guarantee the investor's great performance after fees.

Regarding alpha values, we can statistically state changes based on the Z-test in section 6.6. There is a lack of significant values for the actual changes represented in 6.3.2. However, it builds a foundation of trends for mutual funds when the VIX index is high. Findings raise assumptions of the most active mutual funds to increase their performance after a crisis if stocks are picked successfully. Conversely, failing to pick stocks will substantially decrease the mutual funds' performance. Investors should be careful to decide which mutual fund to invest in since they often compare their performance against a preferable benchmark.

From Table 6.9, we can see alternative investment opportunities in passively managed mutual funds, which deliver performance close to the actively managed mutual funds. After correcting fees, actively managed funds' performance may not perform as presented in section 6.3.2. The differential return, which is the instrument mutual fund managers utilize when measuring their performance and competitors (Vogt, 2021), aggravates in event compared to ex-ante. Findings visualize difficulties to perform better than the benchmark in high volatility markets and uncertainty about the future market situation. Furthermore, Table 6.6 indicates that portfolios' deviations might not result in a more outstanding performance in event. Moreover, when the volatility has decreased in ex-post, investors can expect alpha results to be abnormal if portfolio managers are skilled compared to the benchmark.

The performance of a mutual fund is defined by decisions and trades made by portfolio managers. We can conclude that a positive differential return does not necessarily indicate positive alpha. The alpha must be abnormal after fees to determine actual performance. Further investigation of performance after fees as well as measuring return caused by skill or luck will be essential to bring a precise conclusion.

8 Conclusion

In this thesis, we have inspected mutual funds' active management behavior and presented their performance. The thesis provides findings of mutual funds' reaction to overall market uncertainty, where VIX is used as an instrument for measuring market fear. Intuitively, it would be reasonable to believe that professional portfolio managers possess the abilities to generate higher alpha and returns. However, our findings cannot prove this intuition for periods of high market fear. It is reasonable to expect professionals to exploit opportunities when other investors are uncertain and sell positions that may generate undervalued stocks. However, our findings suggest that Norwegian mutual funds generally provide lower alpha and differential returns than OSEFX in a highly volatile market. Besides, we can report some statistically significant results, but we cannot ascertain them. Moreover, z-statistics can state there is a change in alpha.

We present findings of actively managed mutual funds to readjust their portfolio closer to benchmark in periods of high market fear to limit losses. We can statistically indicate a change in the degree of active management, and findings present trends in more index-related portfolio management in periods of high market fear. Mutual funds with a minor degree of active management can be viewed as closet-indexers delivering more stable performance. Z-tests report statistically significant changes, but we struggle to describe the changes precisely.

A private investor can expect a change in the mutual fund portfolio and loss limiting strategies when fund distributors are uncertain about financial markets and high VIX values. Investors of mutual funds should bear in mind that distributors of mutual funds might choose appealing benchmarks to their performance and not visualize the actual difference against a passive investment alternative.

To conclude, our findings report changes in the degree of active management for periods of high market fear. It varies in portfolio managers' decisions to exploit opportunities within periods affected by uncertainty. Moreover, our findings indicate that most mutual funds adjust their portfolio closer to the benchmark. The performance is directly affected by decisions made before and within periods of high market fear. Besides statistically significant changes in alpha and R^2, we struggle to estimate these changes precisely. However, the general conclusion is to expect changes to occur because of high market fear.

9 Limitations and Further Research

The findings in the thesis reflect several trends of what to expect from mutual funds and portfolio managers when the financial market and environment are experiencing market fear. Nevertheless, our findings can indicate trends, but there are still limited factors and various opportunities for further research.

In order to reflect market fear, the VIX index has been used as an instrument for determining periods to be included in the analysis. Unfortunately, the VIX index is limited since it is constructed on American options trading. However, the NOVIX[11] can be used to measure mutual funds restricted geographically to Norway. Unfortunately, the NOVIX is not efficient in absorbing information for the whole time-period. Even if the index is more efficient today, it is not historically optimal (Bugge et al., 2016). This index might be favorable for future analysis.

Some of the periods extracted are 10-13 years old. Due to technological development and other regulations, the financial market has changed over time. These factors will vary with time, and the analysis can be outdated and not exemplary for future periods. However, our findings represent historical changes in mutual funds and might be a baseline for further research in a situation with high market fear in the future.

The mutual funds presented are randomly selected but may be too narrow in order to generalize the Norwegian mutual fund market. For further research, it will be appropriate to consider a larger population scale. Each fund is unique and will operate differently. By enlarging the population's size of existing mutual funds throughout the whole time-period, we will get a more specific view of how the funds are operating and thus minimize selection and survivorship bias.

[11] Norwegian Volatility Index.

We experienced limitations in our data set in the form of not knowing the portfolio composition. Our analysis is solely based upon daily observations at the funds' NAV. Besides our research questions focusing on changes in mutual funds, limitations exist on how precisely we can interpret the changes. For further research, we will recommend collecting the mutual fund's composition of stocks. It is possible to measure active management by active share by having this available. Knowing the portfolio composition will give a deeper insight into how the portfolio is constructed and the actual changes.

The additional research questions focused more on the results from the changes of high market fear. After a period of high market fear, the performance achieved by mutual funds might say something about the actual decisions made. We have introduced stock picking, where we conclude the performance of a mutual fund is reliant on active management and the portfolio manager's ability to pick stocks. Further research on mutual fund performance might utilize theory about skill versus luck to achieve actual performance results.

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Appendix

A1 Summary Statistics

Table A1.1: Summary Statistics

The table presents summary statistics for mutual funds and indices used in the analysis throughout the entire sample period (2006 to 2020). The summary statistics are calculated from the variables' NAV. Column 1 shows the number of observations in each variable. Column 2 displays the variables' mean. Column 3 presents the median of the variables. Column 4 provides standard deviations. Columns 5 and 6 show the variables' smallest and largest values throughout the period.

Statistics	N	Mean	Median	St. Dev	Min	Max
Alfred Berg	3909	19038.8	14232.8	10244.2	4988.8	49432.3
Danske Bank	3864	14715.2	11342.2	8016.3	4119.5	40199.8
DNB	3866	428.1	403.2	133.1	151.0	785.4
Eika	3871	3919.5	3725.2	1143.7	1422.8	6765.5
KLP	3795	4541.9	4116.4	1715.8	1414.0	9236.7
Nordea	3866	1543.2	1349.2	645.9	448.9	3319.4
ODIN	3909	2495.0	2315.4	749.3	1078.7	4872.3
Pareto	3844	5429.1	4959.6	1886.9	1959.5	10862.2
Storebrand	3908	232772.7	202872.5	96318.5	67348.2	497300.9
OSEFX	3901	567.9	521.5	212.6	172.0	1171.7
VIX	3812	19.5	16.8	9.5	9.1	82.7
Alfred Berg Index	3893	255.5	229.6	94.5	84.2	511.4
KLP Index	3804	1794.1	1669.5	657.5	587.1	3563.8

A2 Tables Including One-Factor Regression

Table A2.1: Period 1 SFM and FFC Output

The table below shows the mutual funds' R-squared and annualized alpha throughout the three periods within Period 1. Each period has two main columns (Single-factor and Four-factor), and two columns (R^2 and α) within the main columns. The Single-factor column represents the multiple funds' R^2 and α using only the excess return of OSEFX as factor. The Four-factor column represents the multiple funds' R^2 and α when also applying the factors SMB, HML and PR1YR. The alpha and R-squared values are in percent. Each period is ranked by the funds' R-squared in FFC, from lowest to highest R^2 value. The values in parenthesis are corresponding t-statistics. Significance levels *p <0.1; **p <0.05; ***p <0.01.

Period 1

Ex-ante	Single-factor		Four-factor	
	R^2	α	R^2	α
ODIN	75.0%	-24.86%*	80.6%	-20.38%*
		(-1.84)		(-1.69)
Alfred Berg	87.4%	-12.94%	89.4%	-7.71%
		(-0.85)		(-0.54)
Pareto	88.2%	-7.04%	89.8%	-3.25%
		(-0.58)		(-0.29)
Eika	92.4%	-13.89%	93.2%	-11.63%
		(-1.36)		(-1.19)
Danske Bank	92.4%	-26.27%***	93.6%	-23.41%**
		(-2.67)		(-2.57)
KLP	96.9%	-4.32%	97.1%	-2.95%
		(-0.63)		(-0.44)
DNB	97.5%	4.85%	97.7%	5.23%
		(0.68)		(0.75)
Nordea	98.3%	-6.14%	98.3%	-5.92%
		(-1.09)		(-1.04)
Storebrand	98.3%	-1.57%	98.4%	-1.26%
		(-0.27)		(-0.22)

Event	Single-factor		Four-factor	
	R^2	α	R^2	α
ODIN	66.1%	-23.42%	70.7%	-20.59%
		(-0.82)		(-0.76)
Pareto	90.6%	10.28%	91.1%	12.35%
		(0.51)		(0.61)
Alfred Berg	93.7%	-10.26%	94.0%	-9.51%
		(-0.57)		(-0.53)
Danske Bank	96.2%	5.10%	96.6%	4.17%
		(0.39)		(0.33)
KLP	96.5%	4.00%	96.7%	7.40%
		(0.26)		(0.48)
Eika	97.6%	12.74%	97.7%	14.43%
		(1.00)		(1.15)
DNB	98.0%	15.74%	98.3%	14.23%
		(1.25)		(1.18)
Storebrand	99.4%	5.69%	99.4%	5.58%
		(0.84)		(0.81)
Nordea	99.6%	5.79%	99.6%	5.66%
		(1.08)		(1.05)

Ex-post	Single-factor		Four-factor	
	R^2	α	R^2	α
ODIN	67.7%	12.48%	70.0%	5.83%
		(0.97)		(0.45)
Pareto	86.3%	13.26%	86.7%	11.13%
		(1.25)		(1.02)
Alfred Berg	91.9%	10.45%	92.7%	8.51%
		(1.08)		(0.89)
Danske Bank	93.9%	21.73%***	94.0%	21.86%***
		(2.74)		(2.68)
Eika	94.7%	15.67%**	95.0%	11.38%
		(1.98)		(1.43)
KLP	97.9%	12.13%**	98.0%	10.31%*
		(2.33)		(1.96)
DNB	98.4%	1.26%	98.5%	4.47%
		(0.25)		(0.89)
Nordea	99.3%	7.07%**	99.4%	6.53%**
		(2.35)		(2.12)
Storebrand	99.4%	3.74%	99.4%	3.36%
		(1.21)		(1.06)

Table A2.2: Period 2 SFM and FFC Output

The table below shows the mutual funds' R-squared and annualized alpha throughout the three periods within Period 2. Each period has two main columns (Single-factor and Four-factor), and two columns (R^2 and α) within the main columns. The Single-factor column represents the multiple funds' R^2 and α using only the excess return of OSEFX as factor. The Four-factor column represents the multiple funds' R^2 and α when also applying the factors SMB, HML and PR1YR. The alpha and R-squared values are in percent. Each period is ranked by the funds' R-squared in FFC, from lowest to highest R^2 value. The values in parenthesis are corresponding t-statistics. Significance levels *p <0.1; **p <0.05; ***p <0.01.

Period 2

Ex-ante	**Single-factor**		**Four-factor**	
	R^2	α	**R^2**	α
ODIN	60.7%	35.48%	65.2%	37.00%
		(1.45)		(1.51)
Pareto	81.3%	6.44%	82.7%	10.38%
		(0.38)		(0.59)
Alfred Berg	87.1%	-3.56%	88.6%	0.85%
		(-0.24)		(0.06)
Danske Bank	92.1%	-0.98%	92.6%	-1.62%
		(-0.08)		(-0.13)
Eika	93.9%	-1.39%	95.0%	1.34%
		(-0.12)		(0.12)
KLP	95.9%	4.90%	96.2%	5.94%
		(0.53)		(0.63)
Nordea	98.1%	3.10%	98.3%	4.33%
		(0.49)		(0.68)
DNB	98.3%	0.26%	98.4%	0.91%
		(0.04)		(0.14)
Storebrand	99.0%	3.34%	99.1%	3.77%
		(0.70)		(0.77)

Event	**Single-factor**		**Four-factor**	
	R^2	α	**R^2**	α
ODIN	79.8%	-31.94%	88.0%	22.01%
		(-0.69)		(0.56)
Pareto	93.0%	-21.63%	94.3%	-7.61%
		(-0.84)		(-0.29)
Alfred Berg	95.8%	-26.81%	96.9%	-16.67%
		(-1.18)		(-0.78)
Danske Bank	97.3%	8.76%	98.3%	22.00%
		(0.50)		(1.40)
Eika	98.2%	-22.74%	98.5%	-12.72%
		(-1.49)		(-0.83)
KLP	98.7%	-5.11%	99.1%	2.42%
		(-0.40)		(0.20)
Nordea	99.1%	-5.21%	99.1%	-5.69%
		(-0.48)		(-0.48)
DNB	99.5%	3.96%	99.6%	2.53%
		(0.52)		(0.32)
Storebrand	99.7%	-7.83%	99.8%	-10.48%
		(-1.27)		(-1.61)

Ex-post	**Single-factor**		**Four-factor**	
	R^2	α	**R^2**	α
ODIN	73.4%	-20.26%	76.9%	-19.51%
		(-0.90)		(-0.88)
Pareto	84.4%	8.38%	85.0%	7.39%
		(0.42)		(0.36)
Alfred Berg	90.4%	2.35%	91.3%	4.66%
		(0.13)		(0.26)
Danske Bank	94.3%	-13.21%	95.2%	-12.05%
		(-0.95)		(-0.90)
Nordea	97.1%	-5.41%	97.4%	-5.10%
		(-0.51)		(-0.49)
KLP	97.9%	-15.93%	98.0%	-15.65%
		(-1.81)		(-1.74)
Eika	98.0%	-9.90%	98.3%	-9.23%
		(-1.18)		(-1.15)
DNB	98.7%	-9.11%	98.8%	-9.70%
		(-1.27)		(-1.30)
Storebrand	99.1%	5.63%	99.2%	6.05%
		(0.95)		(0.98)

Table A2.3: Period 3 SFM and FFC Output

The table below shows the mutual funds' R-squared and annualized alpha throughout the three periods within Period 3. Each period has two main columns (Single-factor and Four-factor), and two columns (R^2 and α) within the main columns. The Single-factor column represents the multiple funds' R^2 and α using only the excess return of OSEFX as factor. The Four-factor column represents the multiple funds' R^2 and α when also applying the factors SMB, HML and PR1YR. The alpha and R-squared values are in percent. Each period is ranked by the funds' R-squared in FFC, from lowest to highest R^2 value. The values in parenthesis are corresponding t-statistics. Significance levels *p <0.1; **p <0.05; ***p <0.01.

Period 3

Ex-ante	**Single-factor**		**Four-factor**	
	R^2	α	**R^2**	α
ODIN	67.7%	-42.27%**	71.0%	-42.41%**
		(-2.02)		(-1.98)
Alfred Berg	84.7%	-30.17%*	86.6%	-41.07%**
		(-1.85)		(-2.48)
Pareto	90.2%	-8.15%	90.3%	-7.50%
		(-0.65)		(-0.55)
Danske Bank	92.4%	-4.69%	93.7%	-13.93%
		(-0.39)		(-1.17)
Eika	93.9%	-18.98%*	94.4%	-21.50%*
		(-1.65)		(-1.80)
KLP	97.7%	1.14%	97.9%	3.28%
		(0.16)		(0.44)
Nordea	98.3%	-2.18%	98.6%	-6.12%
		(-0.36)		(-1.02)
Storebrand	98.6%	-1.18%	98.7%	-1.92%
		(-0.21)		(-0.32)
DNB	99.0%	5.89%	99.0%	6.19%
		(1.24)		(1.21)

Event	**Single-factor**		**Four-factor**	
	R^2	α	**R^2**	α
ODIN	80.2%	-67.23%*	81.9%	-55.38%
		(-1.80)		(-1.47)
Eika	92.4%	-31.82%	92.9%	-34.20%
		(-1.12)		(-1.19)
Pareto	92.4%	-25.53%	93.1%	-17.41%
		(-1.00)		(-0.68)
Danske Bank	94.1%	11.75%	94.2%	13.01%
		(0.50)		(0.53)
Alfred Berg	95.8%	-27.48%	96.2%	-32.19%
		(-1.37)		(-1.60)
KLP	98.8%	-7.96%	98.8%	-4.85%
		(-0.72)		(-0.43)
Nordea	99.1%	0.92%	99.2%	1.00%
		(0.10)		(0.10)
DNB	99.4%	10.51%	99.5%	10.70%
		(1.38)		(1.37)
Storebrand	99.6%	-0.74%	99.6%	-0.77%
		(-0.12)		(-0.12)

Ex-post	**Single-factor**		**Four-factor**	
	R^2	α	**R^2**	α
ODIN	74.6%	9.87%	78.3%	16.49%
		(0.40)		(0.69)
Pareto	91.8%	-0.17%	94.5%	-2.53%
		(-0.01)		(-0.17)
Danske Bank	92.2%	27.89%	94.7%	26.16%
		(1.48)		(1.60)
Alfred Berg	95.0%	11.95%	95.5%	8.66%
		(0.84)		(0.61)
Eika	97.0%	-9.87%	97.9%	-7.05%
		(-0.85)		(-0.70)
KLP	98.0%	-1.72%	98.5%	-0.16%
		(-0.17)		(-0.02)
Nordea	98.4%	0.80%	98.9%	-0.21%
		(0.09)		(-0.03)
DNB	99.5%	3.96%	99.6%	1.70%
		(0.79)		(0.36)
Storebrand	99.5%	-1.76%	99.6%	-3.72%
		(-0.33)		(-0.78)

Table A2.4: Period 4 SFM and FFC Output

The table below shows the mutual funds' R-squared and annualized alpha throughout the three periods within Period 4. Each period has two main columns (Single-factor and Four-factor), and two columns (R^2 and α) within the main columns. The Single-factor column represents the multiple funds' R^2 and α using only the excess return of OSEFX as factor. The Four-factor column represents the multiple funds' R^2 and α when also applying the factors SMB, HML and PR1YR. The alpha and R-squared values are in percent. Each period is ranked by the funds' R-squared in FFC, from lowest to highest R^2 value. The values in parenthesis are corresponding t-statistics. Significance levels *p <0.1; **p <0.05; ***p <0.01.

Period 4

Ex-ante	Single-factor		Four-factor		*Event*	Single-factor		Four-factor		*Ex-post*	Single-factor		Four-factor	
	R^2	α	**R^2**	α		**R^2**	α	**R^2**	α		**R^2**	α	**R^2**	α
Alfred Berg	82.8%	31.02%*	85.6%	23.97%	**Danske Bank**	93.0%	1.98%	95.3%	0.64%	**Danske Bank**	87.4%	30.97%	89.3%	22.86%
		(1.72)		(1.35)			(0.06)		(0.02)			(1.59)		(1.20)
Danske Bank	84.1%	22.81%	87.7%	16.10%	**Nordea**	88.4%	-16.26%	95.9%	-15.53%	**Alfred Berg**	85.4%	32.78%*	89.6%	23.59%
		(1.43)		(1.06)			(-0.37)		(-0.53)			(1.92)		(1.54)
Pareto	89.6%	0.72%	92.0%	6.91%	**Pareto**	93.8%	-21.85%	97.3%	1.82%	**Nordea**	89.9%	24.41%	91.6%	16.62%
		(0.06)		(0.63)			(-0.66)		(0.07)			(1.52)		(1.07)
ODIN	92.8%	4.97%	93.6%	5.02%	**ODIN**	96.6%	-16.19%	97.8%	-1.29%	**Pareto**	88.0%	-5.81%	93.6%	-10.79%
		(0.52)		(0.52)			(-0.73)		(-0.07)			(-0.28)		(-0.67)
Nordea	89.3%	-1.76%	94.5%	2.11%	**Alfred Berg**	95.0%	7.75%	98.1%	-5.26%	**Eika**	95.1%	-3.78%	95.5%	-7.29%
		(-0.13)		(0.21)			(0.28)		(-0.28)			(-0.35)		(-0.68)
Eika	94.9%	-5.45%	96.5%	-1.26%	**Storebrand**	97.9%	-0.81%	98.3%	-7.50%	**ODIN**	95.0%	3.47%	96.4%	0.34%
		(-0.70)		(-0.18)			(-0.05)		(-0.44)			(0.28)		(0.03)
Storebrand	94.6%	6.16%	96.5%	6.58%	**KLP**	98.0%	-1.40%	98.6%	5.31%	**KLP**	96.4%	8.05%	96.6%	9.12%
		(0.66)		(0.81)			(-0.08)		(0.32)			(0.73)		(0.80)
KLP	95.8%	-12.25%	96.2%	-8.88%	**Eika**	98.1%	-5.66%	98.7%	-19.50%	**Storebrand**	95.8%	12.75%	97.1%	5.37%
		(-1.43)		(-1.01)			(-0.39)		(-1.43)			(1.09)		(0.52)
DNB	96.8%	-14.71%**	97.2%	-15.36%**	**DNB**	98.0%	-0.30%	98.8%	13.72%	**DNB**	97.2%	-5.24%	97.7%	-6.55%
		(-2.01)		(-2.11)			(-0.02)		(0.89)			(-0.52)		(-0.67)

A3 Z-statistics

Table A3.1: Alpha Z-statistics

	Period 1	Period 2	Period 3	Period 4
Alfred Berg	-6.24	-5.10	-10.78	-2.31
Danske Bank	0.68	5.34	3.30	-0.71
DNB	6.96	0.74	3.17	3.85
Eika	7.79	-3.32	-10.63	-5.76
KLP	3.32	0.43	-1.67	1.30
Nordea	2.34	-1.66	0.03	-4.62
ODIN	-12.65	7.73	-21.11	-0.05
Pareto	6.15	-2.55	-6.24	0.16
Storebrand	1.89	-2.72	-0.57	-2.27

Table A3.2: R^2 Z-statistics

	Period 1	Period 2	Period 3	Period 4
Alfred Berg	2.32	1.98	2.07	2.57
Danske Bank	3.89	2.46	1.54	1.82
DNB	0.35	0.50	0.55	0.36
Eika	1.93	1.21	-0.36	1.39
KLP	-0.04	0.58	0.60	0.51
Nordea	1.78	0.78	0.93	-0.02
ODIN	-3.97	3.74	2.01	7.87
Pareto	2.56	2.21	2.20	3.43
Storebrand	6.51	3.41	3.95	3.45