Hans Markus Braaten

Under what circumstances can active fund management in Norway outperform passive investment strategies?

An empirical study of Norwegian mutual fund management & performance

Master's thesis in Economics & Business Administration - Major in Finance & Investments
Supervisor: Christian Ewald
May 2022

Master's thesis

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Preface

This master thesis is written as the final chapter of my master's degree in Economics & Business Administration at NTNU Business School, with a major in Finance & Investments.

In the autumn of 2021, I began to delve into which topic to choose. To create my own diversified portfolio while managing the level of risk, has been a great hobby of mine. It sounds so easy, yet so impossible. Over time I have gotten a greater appreciation for fund managers with more detailed reasoning for their portfolio allocations. From my studies I therefore found portfolio management and risk management especially interesting. During the spring of 2022, I have spent a tremendous amount of time working on this thesis. It has been fascinating to combine my hobby with theory, and to understand new aspects of portfolio management.

I would like to thank my supervisor, Professor Christian Ewald, for guidance and advice for the duration of this thesis. Furthermore, I express my gratitude to family and friends for support, patience and understanding. A special thanks also goes out to Thea Amalie Løvøy and her parents.

The content of this thesis is at the author's expense.

Abstract

In this thesis I study the Norwegian mutual funds, with emphasis on how activity, years of experience, risk-level and market conditions impact the performance of these funds. The performance is measured by alpha from a linear regression of the Carhart four-factor model. The analyses contain 84 mutual funds and 8 index funds, with a sample period from 17th of February 2017 to 28th of January 2022. The sample period is also divided into smaller subperiods determined by the level of market risk from the VIX-index.

To start with I examined the gross-return performance of mutual funds for the overall period. The few individual mutual funds that significantly overperformed were not recognizable when rerunning the regressions on groups by level of experience. But there were indications that the least actively managed funds measured by R^2, contained the most experienced fund managers. In fact, all the potential "closet-indexers" I found, were included in the group of high-experienced fund managers.

Further it was necessary to understand how the mutual funds were impacted by changes in market conditions. When market volatility was lower, the activity amongst all mutual funds increased. From both the Sharpe Ratio and the factor bets, it seemed that mutual funds reduced their risk during such circumstances, but the R^2 also indicated more active positions in unknown factors. However, all fund-groups provided insignificant alphas.

With increased volatility in the market, the activity on the other hand reduced. While the high-experienced fund managers appeared to be potential "closet-indexers", they were in fact outperforming the market. But the highest performing funds, were the ones with medium-experienced fund managers. Both increased their positions towards the market and reduced their unknown factor bets, but the latter increased even more towards small-cap stocks. Parts of the volatile market was burdened by the "bear-market" of February 2020, causing negative Sharpe Ratios for all fund groups. However, the medium-experienced group were slightly better than the index funds, meaning that these funds reduced their losses and positioned better for future gains. Despite that, all alphas turned out insignificant when I retested the same groups using net-return.

Sammendrag

I denne oppgaven studerer jeg de norske verdipapirfondene, med vekt på hvordan aktivitet, års erfaring, risikonivå og markedsforhold påvirker ytelsen til disse fondene. Ytelsen måles ved alfa fra en lineær regresjon av Carhart fire-faktor modellen. Analysene inneholder 84 verdipapirfond og 8 indeksfond, med en periode fra 17. februar 2017 til 28. januar 2022. Perioden er også delt inn i mindre delperioder bestemt av nivået på markedsrisikoen fra VIX-indeksen.

Til å begynne med undersøkte jeg bruttoavkastningen til verdipapirfond for den totale perioden. De få individuelle verdipapirfondene som signifikant overpresterte, var ikke gjenkjennelige når regresjonene ble gjentatt for grupper etter erfaringsnivå. Men det fantes indikasjoner på at de minst aktivt forvaltede fondene målt ved R^2, inneholdt de mest erfarne fondsforvalterne. Faktisk var alle de potensielle «skap-indeksfondene» jeg fant, inkludert i gruppen av høyt-erfarne fondsforvaltere.

Videre var det nødvendig å forstå hvordan verdipapirfondene ble påvirket av endringer i markedsforholdene. Når markedsvolatiliteten var lavere, økte aktiviteten blant alle fond. Fra både Sharpe Ratio og faktor-vektingene så det ut til at verdipapirfond reduserte risikoen under slike omstendigheter, men R^2 indikerte også mer aktive posisjoner i ukjente faktorer. Alle fondsgruppene ga imidlertid ikke-signifikante alfaer.

Ved økt volatilitet i markedet, reduserte derimot aktiviteten. Selv om de høyt-erfarne fondsforvalterne så ut til å være potensielle «skap-indeksfond», slo de faktisk markedet. Men de best presterende fondene, var de med middels-erfarne fondsforvaltere. Begge økte sine posisjoner mot markedet og reduserte sine ukjente faktor-vektinger, men sistnevnte økte enda mer mot «small-cap» aksjer. Deler av det volatile markedet var tynget av «bear-markedet» i februar 2020, som forårsaket negative Sharpe Ratio for alle fondsgruppene. Den middels-erfarne gruppen var imidlertid litt bedre enn indeksfondene, som betyr at disse fondene reduserte tapene og posisjonerte seg bedre for fremtidige gevinster. Til tross for det, ble alle alfaer ikke-signifikante når jeg retestet de samme gruppene med nettoavkastning.

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1. Introduction

1.1 Motivation

A fund manager's first and foremost task is to achieve higher risk-adjusted returns than the market. Whether a fund yields high or low returns, it needs to be justified by an acceptable level of risk promised to the investors. This is one of the reasons why investors are willing to pay premium for the cost of mutual funds instead of choosing the cheaper index funds. If an investor on the other hand is very risk-averse, one rather tends to choose index funds. But does index funds truly yield better returns based on the risk? By choosing index funds, one automatically decreases risk by the diversification of the portfolio. However, you will not receive the human input of recognizing undervalued stocks or specific markets. In index funds you are also less agile compared to actively managed funds, specifically in terms of quick re-allocations to continuously have a good risk-adjusted return. With the latest correction fresh in mind, and a very volatile market with lots of uncertainties ahead, this agility will from time to time be very favorable to take advantage of. When Covid-19 hit the market in February 2020, some active fund managers did indeed make quick adjustments. This limited somewhat their downside when the stock market fell. In addition, they got a better opportunity to position for a significantly bigger "bull-market" in the time following.

In recent years the public's interest in funds have increased, especially after Covid-19. Low interest rates and travel restrictions has led more of the population to look for alternative placements of their savings. About 46% of the Norwegian population is now invested in funds, while just five years ago this amounted to 34% (VFF, 2021). This increase will boost the liquidity in the market. I therefore find it interesting to see how fund managers performance are affected. Most previous studies have obviously focused on funds in the US stock market, due to its size and popularity. However, with this increase I find it more interesting to study the smaller, less researched Oslo stock exchange.

There are plenty of studies written about actively managed funds and index funds. Specifically, about which are best and if it is worth paying fees over choosing a passive "free" index fund. Results from previous studies I have read, seem to be split in two. Some tilt towards actively funds being the preferred choice, while others indicate the opposite. Even classical finance literature indicates the difficulties in overperformance. The efficient market hypothesis explains how stock prices reflect all available information, thus indicating that no one would be able to pick undervalued stocks. Burton Malkiel (2003) claimed that if the efficient market hypothesis hold, even blindfolded monkeys would prove to be as good stock pickers as professional fund managers. However, there have also been critiques against the efficient market hypothesis claiming that fund managers in fact are better at picking stocks than monkeys. Some studies have highlighted that there is a low share of stocks that yield the total excess return among all stocks. This indicates that fund managers who beat the market need to be skilled. And of course, there are examples of such. Peter Lynch, one of the most successful fund managers in history, generated an annual average return of 29%. But how can one recognize these skilled funds or fund managers?

1.2 Problem statement

In this thesis I want to study if fund managers in Norway, focused on certain key factors, can consistently outperform the market. Can years of experience within the fund define if the performance is based on skill or pure luck? Are there specific periods where mutual fund stands out? By recognizing how different mutual funds operate, can you then learn how to invest in them with a new strategy? The preliminary problem statement is:

> ***Under what circumstances can active fund management in Norway outperform passive investment strategies?***

Furthermore, I include two additional research questions to concretize the focus areas of my original problem statement:

1. How does fund manager activity, experience and risk impact performance?
2. What implications will variations in market conditions have on this?

1.3 Purpose of the thesis

The purpose of this thesis is to challenge the mindset of how one relates to investments in funds. I hope to guide the long going narrow debate of active vs. passive, into a new direction where one rather reflects on a broader range of factors. I seek to elaborate on Norwegian fund managers level of activity, experience and risk. And further examine how the performance are affected by these factors. I hope my results can contribute to how one can invest smarter in funds, by recognizing certain situations where selected funds are the preferred choice. The results will be most useful for academics and private investors. Perhaps also fund managers and their owners find the results interesting.

1.4 Structure of the thesis

In the next chapter I will lay the foundation needed to understand the context of this thesis. I start with a basic introduction of the different types of funds, and the development of the mutual fund market in Norway. I also explain the role of risk and volatility on the market.

Chapter 3 presents the relevant theory and models for portfolio valuation. I explain the background for the topic and how it has progressed over time. This is followed by the theory for defining activity-level, risk-adjusted performance and finally the paradox of market efficiency. *Chapter 4* continues with a review of the most relevant literature and research results on the topic.

Chapter 5 defines the specific methods and regression models I have utilized for my analyses. I also describe why and how the data sample are grouped. In *chapter 6*, I explain how the data is retrieved and present the descriptive statistics. This chapter also illustrates how I fulfill the OLS assumptions presented in chapter 5.

In *chapter 7*, I present all results from my analyses, and discuss the findings compared to previous theory and research. Finally in *chapter 8*, I present my conclusion with comments on limitations and potentials for further research.

2. Clarification of concepts

Before embarking on this thesis, it will be useful to understand the fundamentals of funds and the basic terms in use. It will also be necessary to understand how the stock market fluctuates and its involved risk. In the world of funds, we find private equity funds, hedge funds, pension funds, mutual funds, exchange traded funds (hereby called ETF), etc. In my thesis I focus on publicly available investments, therefore I focus on the open-end mutual funds and ETF's. Among both mutual funds and ETF's there is a cross section, either you choose actively managed funds or passive index funds. Actively managed funds consist of mutual funds and active ETF's. Passive funds consist of index funds and index ETF's.

Mutual funds

Open-ended mutual funds are mutual funds available for everyone to invest in. Mutual funds are actively controlled by a fund manager, who selects different assets the invested capital shall be placed in. Typically, a mutual fund has a chosen benchmark index to compare returns with. Usually there is also specified a certain risk level, based on the assets controlled, that the fund is supposed to work within.

Index funds

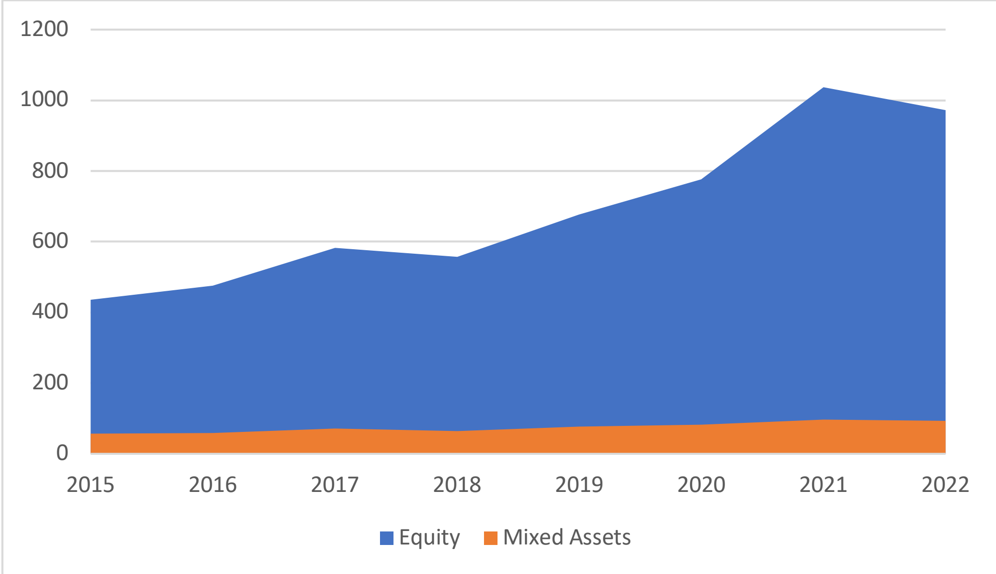
Index funds represents a weighted selection of assets exposed towards certain sectors and/or geographical locations. These are passive funds, meaning that there are little to no involvement of a fund manager.

ETF's

ETF's can either be actively managed or follow some sort of index. Over the years they have become more popular by having the advantage of more similar features to regular stocks. Normal mutual funds or index funds are traded at the end of the day, while ETF's can be traded instantly when the market is open, just like another stock. This feature makes the funds more liquid and thus more popular.

Within the different funds there are several asset classes to be exposed towards: Equity, Money Market, Fixed-Income, Mixed Assets and Other. This study shall focus on equity and mixed assets. Equity is an asset class based on stocks, while mixed assets usually refer to a mix of stocks, bonds, cash and real estate.

Figure 1: Historic asset under management in Norwegian funds



Development of asset under management for equity funds and mixed assets fund measured in billion NOK. Data from 2015 to February 2022, retrieved from VFF. Source: (VFF, 2022)

Figure 1 depicts the increased capital invested in both Norwegian equity- and mixed asset funds. During this period equity funds has increased with 123%, while mixed asset funds has increased with 62%. Further it will be necessary to understand how the market fluctuates.

Volatility

When the market or individual stocks involves high risk, they can either rise or fall randomly in prices within a short period. In finance this is referred to as volatile markets or stocks. There are many methods to illustrate the volatility, in my thesis I will use both standard deviation and beta. The standard deviation is expressed as the square root of the variance between stock price and mean.

$$Standard\ deviation = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}} \tag{1}$$

From equation (1) one can see that the basics of the formula define the volatility by how much the stock price x_i averagely varies for all sub-periods from the mean of the stock price $\bar{x}$ over the complete period. In that sense, a high standard deviation implies high volatility. Standard deviations are presented on an annualized basis. Beta is known within quantitative methods. It has a similar purpose in finance, to give an indication of the correlation between an asset and the market.

$$\beta = \frac{Cov(r_i, r_m)}{Var(r_m)} \quad (2)$$

In equation (2) the $Cov(r_i, r_m)$ is the covariance, meaning the linear relation between stock returns r_i and market returns r_m. $Var(r_m)$ is the variance of the market returns. When the beta is equal to 1, it indicates that the asset is just as risky as the market. A beta greater than 1 indicates a more volatile asset than the market, and vice versa when the beta is less than 1.

Bull & bear markets

There are plenty of definitions for bull & bear markets, where some are very detailed by including certain factors or time horizons needed for verification. In my thesis I simplify these terms by defining a market trending upwards as a bull market, and a market trending downwards as a bear market. In both markets one will find more volatility than in a stable market where you move sideways.

3. Theory

This chapter will be a thorough introduction to the theory used in my thesis. I begin with introducing the basic calculations of returns, followed by how this return will be used for valuation purposes in the different portfolio valuation models. I will explain both the benefits and drawbacks of the models, and theory behind them. The models will be used for regression analyses on the data for mutual fund returns. This will provide further measurements for performance and risk. After this foundation, I will explain the difference in active and passive management, and how I will differentiate between them. Finally, I introduce the market efficiency and its paradox.

3.1 Returns

Returns within the stock market are created from taking advantage of opportunities. A fund manager needs to locate stocks with great profitability, that can increase in value or pay dividend. This can also include to locate the undervalued stocks which can be reprised, and thus generate higher returns. Often one rather refers to the excess return, the rate of return adjusted for an alternative risk-free position.

$$Excess\ return = r_i - r_f \tag{3}$$

In equation (3) r_i is the return of the risky asset and r_f is the return of the risk-free rate. Excess return can also be used to compare a risky investment with another alternatively risky investment, say investing in a mutual fund compared to a passive index fund.

To evaluate the performance of a portfolio, the excess return won’t be a good enough predictor. Methods for evaluating the risk-adjusted performance are more utilized. Individual assets have risk exposure and will thus have volatility depending on how risky the asset is. A portfolio is based on multiple risky assets, and thus a portfolio will be exposed to a combination of this volatility. A measurement to adjust the returns for the risk taking of fund managers would then be necessary. Jensen’s alpha and Sharpe Ratio are such measurements and will be introduced in the coming sections.

3.2 Introduction to models

3.2.1 CAPM

The capital asset pricing model (Hereby called CAPM) was developed independently during the 1960's by Treynor (1962)[1], Sharpe (1964), Lintner (1965) & Mossin (1966). It has since been a widely used model in valuation of portfolio and stocks. It was a simple model with the intention to create optimal portfolios based on Markowitz's (1959) work with diversification of portfolios. As the model is mainly theoretical, it has some assumptions that simplifies the reality. It assumes there is a quadratic utility function, meaning that investors are risk-averse and maximizes the mean-variance criterion. The criterion is a utility maximization problem, where an investor wants to maximize returns for a given risk-level measured in variance. The CAPM also assumes investors have identical decision horizons, a homogeneous expectation and that there is a risk-free rate for all investors to borrow or lend at. And finally, it assumes that there are perfect markets with no taxes or transaction costs, and all information is accessible to everyone. CAPM is presented in equation (4) as:

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f] \tag{4}$$

Where: $E(r_i)$ is the expected return for asset i, r_f is the risk-free rate, $E(r_m)$ is the expected return on the market portfolio. $[E(r_m) - r_f]$ is then the expected excess return of the market portfolio. As introduced in equation (2), β_i indicates how volatile or risky the asset is compared to the market portfolio.

As seen in Figure 2 below, portfolio risk is interpreted as: *Total risk = Systematic risk + unsystematic risk*. Systematic risk is explained as the risk related to the economy, while the unsystematic risk is the risk linked to each specific asset. In this way the unsystematic risk can be minimized with diversification of the portfolio. The beta in equation (4) is related to the systematic risk, and thus explains the risk which cannot be minimized with diversification.

[1] The development of CAPM has usually been credited to Sharpe, Lintner and Mossin. But the unpublished articles of Treynor, which predates the others, also deserves recognition. Craig W. French (2003) published a description of the Treynor CAPM including Treynor's work: "Market Value, Time and Risk" (1961) & "Toward a theory of market value of risky assets" (1962).

Figure 2: Portfolio Risk

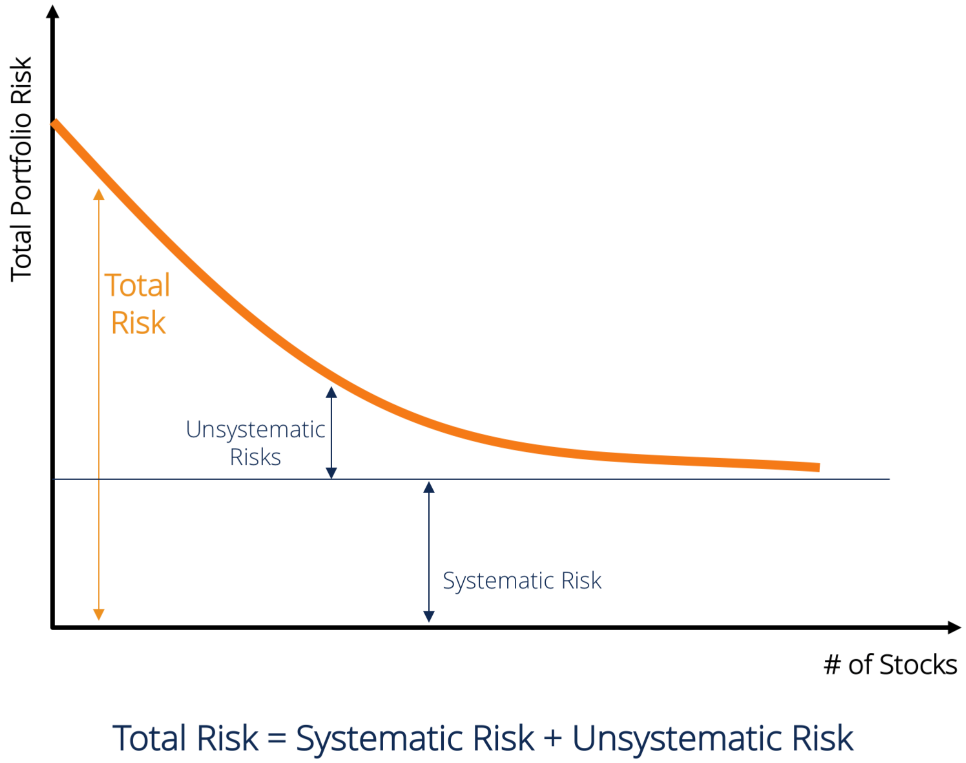


Figure retrieved from Corporate finance institute. Source: (Corporate finance institute, 2022b)

The formula for total risk is expressed in equation (5). With an increasing number of assets in a portfolio, the variance approaches the average covariance. What is left in such an example is only the systematic risk *($\beta_i^2 \times \sigma_m^2$)*. The unsystematic risk $[\sigma_i^2 - (\beta_i^2 \times \sigma_m^2)]$ is then the difference between the two.

$$\sigma_i^2 = \beta_i^2 \times \sigma_m^2 + \sigma_{\varepsilon i}^2 \tag{5}$$

3.2.2 Jensen's alpha

Jensen was early to point out one of the flaws of the Sharpe-Lintner version of CAPM. He expressed that the model would only work for unmanaged portfolios, as it won't account for predictive skills (Jensen, 1968). The matter is the relation between expected return and market beta implying a time-series regression, in which explains the excess return to be completely reliant on the risk premium of the market. In this case if the fund manager has predictive skills, the constant error term would need to be indifferent from zero.

$$r_{it} = r_{ft} + \beta_i[r_{mt} - r_{ft}] + \varepsilon_{it} \tag{6}$$

$$r_{it} - r_{ft} = \beta_i[r_{mt} - r_{ft}] + \varepsilon_{it} \tag{7}$$

Jensen visualizes this by transferring the risk-free rate r_{ft}, from the right-hand side in the CAPM from equation (6) to the left-hand side seen in equation (7). And explains the problem as if a superior forecasting manager is selecting securities, in the view of CAPM, he will tend to systematically select securities which realize $\varepsilon_{it} > 0$ (Jensen, 1968). There was a need for a non-zero constant to explain the excess-return over the risk premium. He thus created what we know today as Jensen's alpha.

$$r_{it} - r_{ft} = \alpha_i + \beta_i[r_{mt} - r_{ft}] + u_{it} \tag{8}$$

In equation (8) the new error term u_{it} is expecting $E(u_{it}) = 0$. Using Jensen's alpha, a superior forecasting manager would select securities which realize $\alpha_i > 0$.

3.2.3 Fama-French three-factor model

Fama & French (1992) published an article which gathered and highlighted the many contradictions of CAPM. They explained that the simple relation between average return and market beta, that was found in CAPM from 1926-1968, disappeared during the period 1963-1990. They believed that the portfolio-returns could be better explained by adding new factors to characterize the stocks and their risk within the portfolio, not only the market. These new factors were used when conducting a new study to observe whether they could accurately describe the returns. This was the origin of the famous Fama-French three-factor model.

The first factor Fama & French (1992) developed was the size factor inspired from Banz (1981). In a later study, Fama & French (1993) renamed this factor to SMB (Small minus big) and defined it as the difference between returns of a portfolio based on small stocks and a portfolio based on big stocks. The second factor was inspired by the ratio of book-to-market value (BE/ME) of Stattman (1980) and Rosenberg, Reid and Lanstein (1985). Fama & French (1993) called this factor HML (High minus low) and defined it as the difference between returns of a portfolio based on stocks with high book-to-market and a portfolio based on stocks with low book-to-market. When these factors are integrated with both CAPM and Jensen's alpha, I find the Fama-French three-factor model in equation (9):

$$r_{it} - r_{ft} = \alpha_i + \beta_i[r_{mt} - r_{ft}] + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_i \tag{9}$$

3.2.4 Carhart four-factor model

Carhart (1997) continued the work off the three-factor model and included yet another factor, Jagedeesh & Titman's (1993) one-year momentum effect. This factor was called PR1YR and captures the momentum effect created by recent price changes in the assets. Carhart (1997) explained it as the difference between previous equal-weight average of the highest 30 percent performing stocks minus previous equal-weight average of the lowest 30 percent performing stocks. Fama & French (2010) has since introduced an updated version of this factor renamed MOM (Momentum) and tested this against the market. They first assigned stocks into six value weighted portfolios of low-, medium- and high momentum groups. After that they could measure the MOM factor by the average returns of two "high momentum" portfolios minus the average returns of two "low momentum" portfolios. MOM included in the three-factor model represents the Carhart four-factor model in equation (10):

$$r_{it} - r_{ft} = \alpha_i + \beta_i[r_{mt} - r_{ft}] + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{MOM}MOM_t + \varepsilon_i \quad (10)$$

3.3 Active vs. Passive

The goal of active fund management is to beat the market, controlled for a specified risk level promised to the investors. The market usually refers to a benchmark index, which is an index from the stock market region they invest in or its industry sector. This is used for both comparing returns as well as a basis for measuring risk. The idea is that a fund manager minimizes its risk in line with the benchmark index, while simultaneously generating higher returns. Some management strategies will be more active, others more passive. Very passive strategies have a tendency of replicating index funds too closely. This is defined as "closet-indexing", indicating that a mutual fund charges higher fees even if it closely imitates its benchmark index.

Measuring the exact activity within funds is extremely demanding, but there are methods for capturing some aspect of the activity. Cremers & Petajisto (2009) split the term active management into "Passive management" and "Active management". They define "Passive management" as replicating the stock holdings and thus the return of an index (Essentially the same as "closet-indexing"). "Active management" is then any deviation from "Passive management". Cremers & Petajisto (2009) further explain two ways active management can outperform a benchmark index, by stock selection or factor timing. Stock selection can be measured with "Active Share", by comparing weights of all stocks in a mutual fund from a benchmark index. Factor timing involves taking broader bets on certain market sectors. Cremers & Petajisto (2009) used “Tracking Error” as measurement for this purpose. It captures the volatility in the fund not explained by movements in the benchmark index.

Access to data on mutual fund compositions and their selected benchmark index are often restricted, making it hard to utilize the “Active Share” method (This is also the case for my thesis). Due to this problem, Amihud & Goyenko (2013) proposed R^2 as a more accessible solution to measure the degree of active management. As my thesis is based on regressed multi-factor models for the already established risk factors in the section above, I will naturally receive an R^2. As with “Tracking Error”, R^2 also measures how much of a conviction is placed on each factor bet. R^2 is a known correlation measurement in regression models and is used to define the explanatory power a specific model has. In the case of a multi-factor model this is based on the allocations of the independent variables. In the topic of fund management activity, the measurement will thus be able to measure how closely the assets variation in a fund, tracks its benchmark index and the other risk factors. With that in mind, R^2 can be used to suspect funds of being “closet-indexers”. Taylor (2004) arguments that R^2 is not necessarily the perfect tool for this purpose. I merely use the measurement to get an idea of activity-levels and to identify potential “closet-indexers”. If the fund has an R^2 equal to 1, then the fund is behaving just as its benchmark index. A lower R^2 indicates that funds are more actively managed, where variations in returns are explained by even broader factor bets than provided. But it also suggests that it is less diversified and takes on more risk. A higher R^2 indicates the opposite, that funds are more weighted towards the market, or in other words more closely replicating the benchmark index.

There is no clear definition on how to use this measurement to explain exactly when a fund is active or not. From previous studies I find that the fine line for defining activity by R^2 has varied from 0.90 and up. Amihud & Goyenko (2013) defined funds with R^2 close to 1.00 as effectively “closet-indexers”. Taylor (2004) used a limit of 0.97. Since Norway is a very small market compared to the rest of the world, and we thus have less opportunities to diversify, the chosen R^2 limit for active mutual funds is 0.97. Above this I will regard as potential “closet-indexers”.

3.4 Risk measurement

When evaluating risk, one tends to view the beta. As introduced in section *3.2 Introduction to models*, beta measures the systematic risk. It measures the undiversifiable volatility for each asset in consideration compared to the market. Thus, it will only explain the investor’s risk for holding a portfolio of stocks over holding the index fund. In this sense beta works well, however this risk measure won't work as a good performance measure. High risk won't necessarily provide high returns, and vice versa. In 1966 William Sharpe (1994) introduced a measure of performance based on both return and risk. The measurement has been renamed and used multiple times, so in 1994 Sharpe combined all versions and provided a more general application for the measurement.

$$Sharpe\ Ratio = \frac{r_p - r_f}{\sigma_p} \tag{11}$$

From the Sharpe Ratio in equation (11) we find the following: r_p is the return of portfolio, r_f is risk-free rate, and σ_p is the standard deviation of the portfolio excess return. When using the excess return, the formula allows for an isolated depiction of the profits directly taking part in the risk-taking activities. The portfolio standard deviation measures how volatile the assets in the portfolio are, or how risky the portfolio is. Further dividing the excess return with the portfolio standard deviation, the Sharpe Ratio will explain if the excess returns are due to risky- or quality investment decisions. The Sharpe Ratio is presented on an annualized basis.

Generally, Sharp Ratios are graded in four categories (Corporate finance institute, 2022a). A Sharpe Ratio lower than 1, is recognized as "Bad". Between 1 and 1.99 is an "Acceptable" Sharpe Ratio. Between 2 and 2.99 is "Good". And finally, a Sharpe Ratio greater than 3 is "Excellent".

3.5 Problem with positive returns and the market efficiency

A central problem to active fund management is the efficient market hypothesis. Eugene Fama (1970) presented this hypothesis as a market with possibilities for investors to choose securities under the assumption that security prices fully reflect all available information. This predicates that all information such as macroeconomics, trends, politics, and news about the individual companies are priced in at any time. In such a world, there would be no chance for an investor to outperform the market by trading based on market timing or buying undervalued stocks. He explains there are three information subsets to reflect prices: weak form, semi-strong form, and strong form (Fama, 1970). Weak form suggest that the information subset is based on historic prices. Semi-strong form suggests that prices are reflected by all publicly available information. And finally strong form, which suggests prices fully reflect all available information. This would include both public and non-public, and such a harsh assumption could be debated, because insiders would know this information before anyone else.

From the information above, one can discuss how accurate it is to assume that investors or analysts won't be able to find good investments. The efficient market hypothesis suggest it would be impossible to do trades or create portfolios which could overperform by recognizing the undervalued stocks. The hypothesis arguments for passive investment strategies to be the only possibility to yield returns, mainly index funds. If this was true, why do we to this day still find plenty of actively managed funds? And why do individual investors try to beat the market?

There have been several articles explaining the paradox in efficient markets. Grossman and Stiglitz (1980) wrote about how investors require compensation for resources used on gathering information. They argued that information comes at a price itself and proposed an information-market equilibrium. At a point where no one has information, there would be high compensations to require more information by doing stock-analysis. If information is available for anyone, the investors who obtained it will lose their compensation. If there is nothing to gain, no one would do stock-analysis, thus the stock prices cannot perfectly reflect the information. The equilibrium would be the point where the initial cost is barely covered by the cost for information. This indicates that you must be a good stock- or market-analyst, in order to generate profit.

4. Literature Review

In this chapter I introduce the most relevant findings from previous research. There have been written plenty of literature and studies about the mutual fund industry, and about the performance of actively managed funds versus the passive index funds. I have thoroughly examined as much literature as possible to highlight the findings that are most relevant for my thesis. I have also investigated more recent studies, to visualizes areas or factors lacking research, where I can contribute.

If an investor selects the option of active fund management, one bumps into a central problem in finance highlighted by Michael Jensen (1968), namely, to evaluate the performance of risky portfolios. He divided the term of portfolio performance in two. First the fund managers ability to identify overperforming securities. And second, their ability to diversify the risk in the portfolio. Jensen emphasized that his use of the term "performance" was only to focus on the predictive forecasting ability, which was the creation of what I previously introduced as Jensen's alpha. The model was supposed to deviate from previous ones, to see if performance could be explained by stock picking skills, or if it was just pure luck. Furthermore, Jensen (1968) tested out his model on a sample of portfolios gathered from the US stock market. His findings indicated that the fund on average were not able to predict security prices, and thus underperformed, especially when considering management expenses. We need to keep in mind that Jensen's results were based on data from a completely different decade, and that the assumptions in CAPM (which his model is based on) are not applicable to real life events.

A more recent study from Bessembinder et al. can support the results of Jensen. They find that the excess value created in the stock market, often relates to the positive outcome of a finite number of stocks (Bessembinder, Chen, Choi, & Wei, 2019). If the fund managers lack the predictive ability to select the few overperforming stocks, the fund will underperform in line with Jensen's results. An argument against these results, is that they used a buy-and-hold strategy. In reality, fund managers will adjust its active positions from time to time in order to yield greater returns. Norang and Augustsson based their master thesis on the same theme as Bessembinder et al. Their study focused on the Norwegian stock market and found similar results. The excess value created, comes from the performance of the top 18 stocks (Norang & Agustsson, 2018). Unless they manage to only pick winner stocks, less diversified active mutual funds will underperform. As a fund manager, you will have to be skilled to be a part of this excess value. It must be mentioned here as well that this study, as with the study of Bessembinder et al., is based on a buy-and-hold strategy.

Another study from USA concluded that skill is crucial for mutual funds to consistently be amongst the top 25% of the top performers over a period of 15 years (Bhootra, Drezner, Schwarz, & Stohs, 2015). But the source for this skill has not been found. Berk & Binsbergen also studied funds in the US market with similar results. They explained that funds in the US with a history of excess-return, continuous to perform well in the coming 10 years (Berk & Binsbergen, 2015). This study shows that investors recognize skill by compensating future performance with higher fees. I also found a study from the Norwegian market, with comparable results. There is evidence for skill amongst Norwegian fund managers, and investors recognize this by investing more capital in the well performing funds (Kolseth, 2014).

Cremers & Petajisto (2009) examined the level of activity within active fund management. They used two combined methods to measure different aspects of activity. “Tracking Error” was used to measure the more overall factor bets of sectors or market timing. The second method was their newly introduced “Active Share”, which compared the weights from a mutual fund’s holdings to the weights of a benchmark index’ holdings. They concluded with results that US mutual funds with high “Active Share” significantly outperforms the market, while “Tracking Error” did not predict higher returns. Unlike “Active Share”, “Tracking Error” provided just marginally significant results, which is why they weighted the “Active Share” results with more trust. Later, Petajisto (2018) conducted a new study on the field. Most mutual funds performed poorly, however the small group with the most active stock pickers beat their benchmark both before and after fees. This result also applied throughout the financial crises between 2008 and 2009. Interestingly he also found that the level of active management was low during high volatility. These results indicate predictive abilities, as well as some fund managers having the ability to identify undervalued stocks.

Amihud & Goyenko (2013) highlighted the difficulties in retrieving fund holding data for the “Active Share” method. To track mutual fund selectivity and/or activity, they rather proposed the more accessible measurement R^2. This resulted in funds with a lower R^2 generated a significantly higher risk-adjusted performance, or alpha. The lower R^2 indicates greater investment activity and/or selectivity within the funds. Among the findings in the article, they compared their results with the “Active Share” method of Cremers & Petajisto. Even though the methods measure activity differently, both provided significant results for the same data sample. Amihud & Goyenko (2013) thus concluded that R^2 is a convenient way one can measure activity and performance without using any other data than mutual fund returns.

Another Norwegian study finds that there is not enough proof that active funds beat the market consistently. On the other hand, they noticed that the fund managers timing ability was consistent, which witness to a good tactical allocation (Grønsund & Lunde, 2010). Interestingly they also found that mutual funds with a history of higher return than the respective index, have lower risk. This contradicts the theory about risk and reward. An investor requires higher returns as a premium for taking on more risk (beta). Indicating that portfolios with constant high returns, should have higher beta than those with lower returns. Recently, chief economist and strategist in Pareto Asset Management (One of Norway's biggest asset management firms) Bergh, claimed that "boring is the new exiting" (Bergh, 2021). Bergh emphasized that since year 2000, stocks with the lowest risk on the Norwegian stock exchange has generated greater returns.

Costa et al. (2006) conducted a study where they tried to see if fund managers work experience could explain how well the mutual fund performed. They used monthly returns of US based mutual funds and tested this against different intervals of work experience. To start with, they found that active fund managers risk-adjusted excess returns are better in bear markets and worse in bull markets. Indicating that fund managers recognize bear market and reallocate accordingly. The obvious would be that experienced managers would do this better than less experienced. But surprisingly they found that fund managers with one year experience or less, performed better in most 36-month periods. The results were only significant for a portion of the subsamples tested, therefore Costa et al. (2006) finds no clear-cut relationship between fund manager experience and performance.

The timing ability is a problematic subject, and as described from the view of the market efficiency, it is impossible. But if one inhabits a constant predictive skill, one will of course have timing ability. In the creation of Jensen's alpha, Jensen (1968) focused on defining the predictive skill, which turned out to yield negative performance results. On the other hand, the results above from Costa et al., indicated that fund managers indeed have timing ability, as they perform better in "bear" periods. A study from Foran & O'Sullivan (2017) focused on identifying timing ability within the UK mutual fund market. They found that when market volatility was higher than normal, a few percentages of funds had lower systematic risk levels. However, they do so at the expense of successful security selection, meaning that returns are lower than the benchmark index. Fleming et al. (2001) conducted a study on the US mutual fund market to measure the value of volatility timing. Unlike Foran & O'Sullivan, they found indications that abnormal returns indeed were due to the ability of volatility timing.

Pàstor et al. (2015) studied the US mutual fund market from 1979 to 2011, where they specifically investigated how the scale of the fund sizes would impact the performance. They found that increasing fund sizes results in decreasing ability to overperform. But interestingly they also found a rising skill level within the active mutual fund industry. This is consistent with the evidence of Philippon and Reshef (2013), which says that education, wage and complexity of tasks in the finance industry has grown steadily since the 80's. Pàstor et al. concluded that increase in skill coincides with the industry growth. The growing industry creates competition which impends fund performance. Finally, they show that fund performance decrease over time, and thus that younger funds overperform older funds. This correlates somewhat to the findings of Costa et al., that fund managers with less experience perform better.

Similar results were found for the mutual fund market in China. Fang & Wang (2015) concluded that those fund managers who performed well with excess return, possessed either an MBA or a CFA. The increasing competition that demands more education, like Philippon and Reshef mentions, forces new fund manager to have a degree. These younger fund managers thus have less experience than the older generation which has a lower degree.

5. Methodology

In this chapter I will present the utilized models, and the choices I have made enabling me to answer my problem statement and research questions. My thesis is an empirical analysis based on a timeseries of rolling returns from both mutual funds and index funds in Norway. The research questions ask to identify performance, activity, experience and risk levels. This will be investigated by utilizing models in regression form. I will begin with an introduction of these models. For the regression models to be valid, they require some assumptions to be fulfilled. I will present a short introduction of these assumptions and the methods used. Further I present how I will compare results for different periods with activity, experience and volatility. Finally, I explain how I will test the robustness of the results.

5.1 Ordinary least square

The chosen method for the regression models is ordinary least square (Hereby called OLS). I will run regression on the weekly excess returns of funds using the following models: Single-factor model, Fama-French three-factor and Carhart four-factor. To select one as the benchmark-model, I will compare the single-factor model to the multi-factor models to see if the funds are more exposed to the additional factors introduced. The single factor model is the CAPM adjusted with Jensen's alpha, and is expressed in equation (12) as:

$$r_i - r_f = \alpha_i + \beta_i\left[r_m - r_f\right] + \varepsilon_i \tag{12}$$

The second model is the Fama-French three-factor model, hereby referred to as the 3-factor, which will account for portfolios to be exposed to more factors than just the market. This one is expressed in equation (13) as:

$$r_i - r_f = \alpha_i + \beta_i\left[r_m - r_f\right] + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_i \tag{13}$$

Finally, the Carhart four-factor model, hereby referred to as the 4-factor, which works almost as the 3-factor, but now also includes exposure to the momentum in the assets. The factor data I gathered used the UMD (Up minus down) version of the momentum factor, which essentially is just renamed from the momentum factor introduced previously by Fama and French (MOM). UMD works just as explained about MOM, displaying the factor to measure the average return of the two high momentum portfolios minus the average return of the two low momentum portfolios (Fama & French, 2010). The 4-factor is expressed in equation (14) as:

$$r_i - r_f = \alpha_i + \beta_i[r_m - r_f] + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_i \tag{14}$$

I will begin with tests for the whole period, followed by additional tests done for shorter time intervals. To answer part of my research questions, I want to investigate whether the mutual funds overperforms overall and/or if there are specific market-condition where the performance stands out. Does fund managers have timing ability? The subperiods will be allocated by the level of the VIX-index. The first period defined low-risk market has a VIX-index below 20%. The second period defined high-risk market has a VIX-index above 20%. In section *6.1 Selection of sample periods,* I present more detailed how the data sample is divided into these low-risk and high-risk periods.

5.2 OLS assumptions

In regression models one must fulfill seven classical assumptions (Studenmund, 2019, p. 111). The regression model must be linear, the mean of the error term must be zero, all explanatory variables are uncorrelated with the error term, no autocorrelation, no heteroskedasticity, no multicollinearity and a normally distributed error term.

If the explanatory variables in fact are correlated with the error term in the 3rd assumption, then it would affect the coefficients, causing a biased result (Studenmund, 2019, p. 113). Both autocorrelation and heteroskedasticity, normally cause OLS to underestimate standard errors. This leads to "too high" t-scores, increasing the chance of rejecting the null hypothesis (Studenmund, 2019, pp. 302, 331). Multicollinearity can on the other hand decrease t-scores, causing p-values to display non-significant explanatory variables while they in reality are significant. A normally distributed error term means that the residuals don't have too extreme values or any skewness in a direction. This is often termed optional, but for small data samples it will be of more importance.

STATA will be used to secure fulfillment of the assumptions. I will test for autocorrelation with the Lagrange Multiplier test, in STATA called the Breusch-Godfrey LM test. White-test will check for heteroskedasticity. Multicollinearity is tested by observing both the correlation coefficient and VIF-indices. To check for normal distributed error terms, I use a joint test for skewness and kurtosis. Later in section *6.4 Fulfilling OLS assumptions*, after the introduction of data, I will provide a deeper insight into which methods I use, and present how all assumptions are fulfilled for my regression models.

5.3 Level of activity – R^2

From the results off the regression models, I will amongst other find the alpha, beta and R^2 for the mutual funds. Alpha and beta are the performance measurement and the risk level. R^2 measures how much variation of a fund's assets are explained by the allocation of assets in the benchmark index and the other factor bets. As introduced in section *3.3 Active vs. Passive*, R^2 will allow me to examine how each fund varies in activity or selectivity and factor bets from a benchmark index. By examining different periods, I will see how this activity changes. Lower R^2 indicates more activity or broader factor bets in the fund's investments, than what the already established risk factors can explain. Higher R^2 indicates less activity by more replication of the benchmark index. The measurement will also allow me to single out the potential "closet-indexers" at the R^2 limit of 0.97. Further I will construct a benchmark model in the same manner as above, but this time using an equal weighted portfolio of index funds instead of mutual funds. The deviation in results of R^2 between the "original" benchmark models of mutual funds and the benchmark model of index funds, will give me a better indication of how actively managed the mutual funds are compared to the true index funds.

5.4 Fund manager experience

I will compare the results from the regression models with the amount of experience the managers have. The complete data on experience for each fund manager was not available, the next best option was the data on fund manager start dates within the specific funds. Just as Costa et. al (2006) did, I created a variable for each fund manager by measuring the duration from the initial start date. This variable is then used as a proxy for mutual fund work experience. Further, work experience is divided into groups for how long a fund manager has worked within the fund:

Low experience: Worked within the fund for up to 3 years

Medium experience: Worked within the fund from 3.1 to 8 years

High experience: Worked within the fund longer than 8 years

I will use these groups to create equal-weighted portfolios to run new regression models on. This will able me to evaluate how fund managers with less experience perform compared to the ones with more experience. I also want to examine whether there is a correlation between how much experience a fund manager has and how actively the fund is managed. And further how much impact this has on the fund performance.

5.5 Sharpe Ratio

To completely understand the performance of mutual funds, I need to evaluate the risk exposure they have towards the assets within. Is the performance due to risk aversion or do the fund managers take on too much risk exposure? The Sharpe Ratio will be used for this purpose. The standard deviation for the individual fund portfolios, provided in subsection *6.2.3 Descriptive statistics – funds*, will be utilized in addition to the excess returns to conduct the Sharpe Ratio described with formula in equation (15):

$$Sharpe\ Ratio = \frac{r_i - r_f}{\sigma_i} \tag{15}$$

I will also assess how all these results vary between different market conditions. The performance, activity level, exposed risk and the market volatility will allow me to conclude whether the fund managers have timing ability or not.

5.6 Robustness test

Will the results be resilient to changes in the groups of experience for the fund managers? I will do a robustness test to see if the results of factor loadings, R^2, alphas, and thus if my conclusion persists with such changes in the data. The fund managers will be regrouped into new levels of experiences:

Low experience: Worked within the fund for up to 3.9 years

Medium experience: Worked within the fund from 4 to 7 years

High experience: Worked within the fund longer than 7 years

6. Data

For my study to be reliable and create the best possible results, I have spent a considerable amount of time on figuring out specifically what data I need and retrieving this data. If fund return data is flawed in some sort of way, it will damage the whole result of my thesis. With that in mind, I emphasize that my data samples are based on quality sources. I have used Thomas Reuters Refinitiv Eikon as my primary source. In addition, I used Morningstar as a secondary source to confirm that both the data on work experience and operating expenses within each fund are correct. The risk-free rate is retrieved from Norges Bank. The factor data is retrieved from the global investment management firm AQR. After the introduction of data, I illustrate that the data gathered provides a valid regression model.

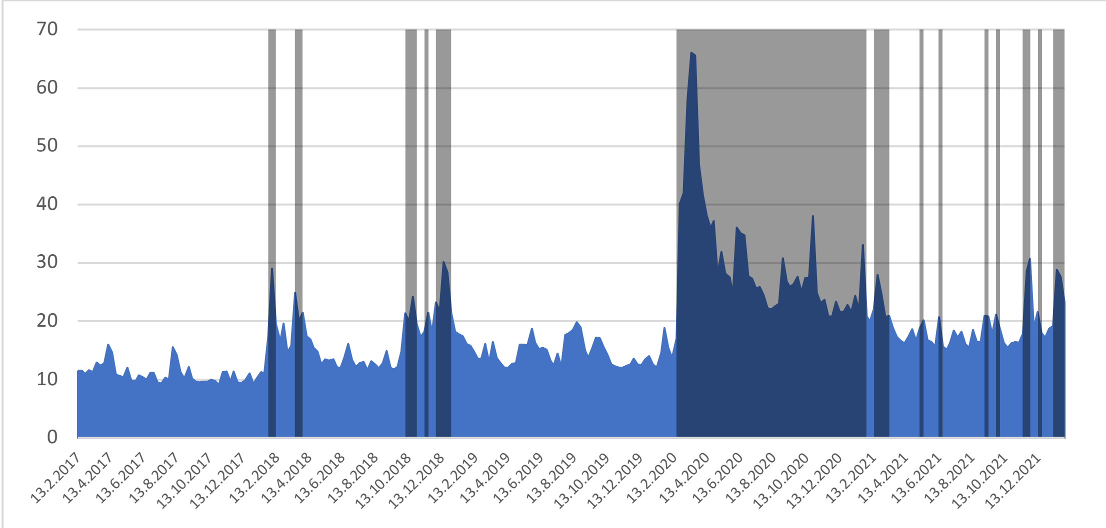
6.1 Selection of sample periods

The overall time horizon is selected based on how many observations I need for a sufficient data sample, as well as what data is available. Because I want to study more frequent activity within the funds, I chose weekly returns. To have enough weekly data I therefore wanted a time horizon of 5 years. The weekly fund data I was able to retrieve reached back maximum 5 years. From the time I retrieved the data, it reached from mid-February 2017 until mid-February 2022. The factor data on the other hand was only updated until 31st of January 2022, and with the weekly dates I find the final date to be 28th of January 2022. This restricted my time horizon of about two weeks. My overall selected sample period therefore dates from 17th of February 2017 to 28th of January 2022.

I have additionally chosen to do individual tests based on the markets risk level[2]. I want to evaluate the fund managers performance in high-risk environments versus normal circumstances. The sample period is thus divided into high- and low volatility periods. Historically the average VIX-index varies between 18% and 20%, depending on the time horizon measured. For this sample period I find an average of 18.20%. A VIX-index of 20% or higher is generally described as a volatile market, while lower indicates a "healthy" market (Corporate finance institute, 2022c). Beneath in Figure 3, the splits in sample periods are illustrated by the shading of grey and white areas.

[2] The original idea was to create dummy variables for the VIX-index and include this in the regression of the multi-factor models. However, when running this I encountered problems with the econometrics. I therefore selected the method of splitting the sample in these subperiods.

Figure 3: VIX-index



The graph illustrates the historic VIX-index. The white areas illustrate periods where the VIX-index are lower than 20%. The grey shading illustrates when the VIX-index are equal to 20% or higher.

6.2 Selection of funds

Thomas Reuters Refinitiv Eikon has a complex database of almost every detail you can imagine about mutual funds. There are plenty of ways to retrieve returns on mutual funds, but the one fitting my study is the rolling performance with weekly data. The rolling performance also include the income yield from dividends reinvested or interest payments. To get an overview of the data sample, I first needed to set some ground rules for what data was necessary to include in my analyses.

6.2.1 Mutual fund criteria's

There is an abundance of different sorts of funds. In Thomas Reuters Refinitiv Eikon you can select different factors to include or exclude data from the sample. To give an in-depth answer to my research questions, I have created a list of fund criteria's that needs to be fulfilled if they are to be included in my data sample:

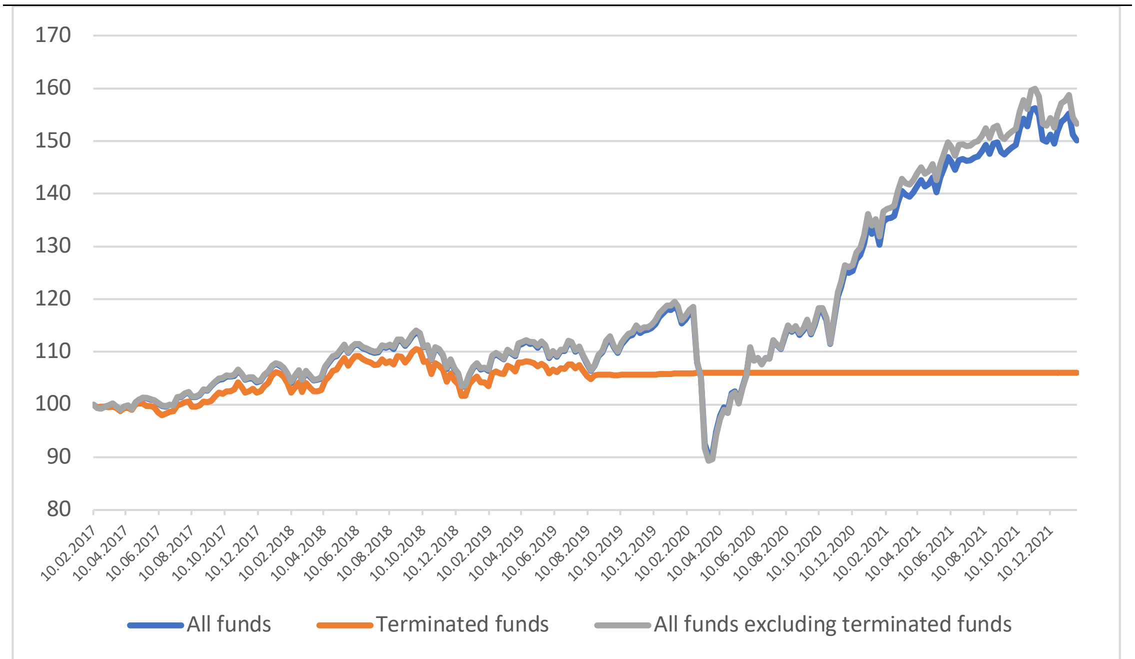
1. The funds are publicly available, thus the asset universe needs to be open-ended mutual funds or ETF's.
2. Asset type can be both equity and mixed assets.
3. Asset status will include active-, merged- and liquidated funds.
4. The mutual funds don't include index in the name.
5. The mutual funds must be actively managed, except for the data on index funds.
6. Both the domicile and geographical focus is Norway.

As for the asset type, I did not want to exclude the mixed assets, because there are many mutual funds also exposed towards rents as a hedge. To prevent biases like survival bias, I chose to include all the versions of asset status.

6.2.2 Survivorship bias

Survivorship bias occurs when bad performing funds are excluded from the data sample. This creates a false representation of the overall performance, by indicating a greater performance. Such bad performing funds are usually merged or liquidated, and it is therefore easy to forget them. As an investor you don't know if a fund performs poorly in the future, let alone if it is terminated. To provide a realistic result, it is therefore important to not exclude these. During the period of my data sample, I find six funds who are either merged or liquidated. Beneath in Figure 4, I have created a graph with three equal weighted portfolios. This illustrates how all mutual funds have performed over the period compared to when terminated funds are excluded from the sample. In this graph, "Terminated" includes both merged and liquidated funds.

Figure 4: All funds vs. Terminated funds



The figure presents three equal-weighted portfolios for their weekly returns over the total sample period.

The terminated funds performed worse, which clearly has a negative effect on performance when included in "All funds". The performance when excluding the terminated funds is a perfect example of survivorship bias. In my analyses I include all funds to prevent this survivorship bias. The exception are funds with less than 30 observations, to maintain sufficient data.

Survivorship bias is also taken under consideration for index funds. I find that of all index funds only "Pluss Indeks" merged in the sample period, probably because this index fund performed worse compared to the others (See *Appendix 2*). I will therefore include this fund, to prevent survivorship bias. An additional comment is that the index funds are not vital for the performance results. They are only to be used as a benchmark for activity levels. This level will be low regardless of the performance, due to the nature of index funds.

6.2.3 Descriptive statistics – funds

At first, I found 136 mutual funds and 11 index funds that met my criterions. Further I selected the data fitting my sample period and cleared for missing or flawed data. Additionally, I found it necessary to make some exclusions which I will explain more in depth. The final dataset for my analyses consists of 84 mutual funds and 8 index funds.

In *Appendix 1*, I present a table with information about the fund's total net assets (TNA), operating expenses and years of experience. Usually one would use "Asset under management" to measure the size of the funds. This measure was not available in Thomas Reuters Refinitiv Eikon, so I rather use "Total net assets" for this purpose. There are some funds with no value and some with extremely low outliers which seem flawed. But on average fund TNA is 331 mill USD. The costs for mutual funds show an average annual total expense of 1.19%, excluding the performance fee. In general, performance fee is an additional cost when a mutual fund reaches a certain goal of performance. Index funds are of course cheaper at 0.23%. Work experience is measured by how long a fund manager has worked within the specific fund. The experiences range between half a year and up to a little over 25 years. For the groups of experiences, I find that 31 fund managers have "Low experience". 24 fund managers have "Medium experience". And 29 fund managers have "High experience".

From the table in *Appendix 2,* I present the descriptive statistics for both mutual funds and index funds. For the mutual funds the number of observations varies between 30 and 259. While for index funds most have 259 observations, except for "Pluss Indeks", which merged in 2021 and thus have less observations of 254. The variations in observations are due to different lifetime cycles, some funds are newly listed, others are older or even terminated. As for the funds I excluded, this was done to ensure that the funds were available for all investors and to secure a sufficient amount of data observations. All funds were publicly available, yet some demanded minimum initial investments of millions of NOK. To guarantee that these funds are available to non-millionaire investors as well, I exclude funds with minimum initial investments of higher than 100 000 NOK. By using the limitation of 30 observations, I ensure that each fund also provides a solid amount of data. All in all, the mutual funds averaged with 183 observations.

All data on returns are presented as gross returns. For the weekly average return of all mutual funds, I find that they on average yield 0.23%. Converting this to annualized return they yield on average 12.69%. The fund "Delphi Norge N" provides the best weekly average return of 0.47%. On the negative side I find "XACT Derivat Bear", which was an active ETF, with the poorest performance of -0.64% weekly loss. This actively managed ETF merged in 2017, most likely due to bad performance. Further I find that the weekly standard deviation also fluctuates a lot between the funds. At the lowest the standard deviation is only 0.10% and 4.20% at the highest. On average it is still relatively high at 2.15%. This indicates a lot of volatility (Especially considering that these are weekly data), which is reflected in the average minimum of -12.78% and average maximum of 6.56%.

For index funds "Storebrand Indeks – Norge A" has the highest weekly average return of 0.24%, while the merged "Pluss Indeks" performed worst with 0.21%. On average all index fund yields weekly average returns of 0.23%, equal to what I found for the mutual funds. Thus, annualized average returns are also 12.69% for index funds. I need to emphasize that the only purpose of the table in *Appendix 2,* is to introduce the essential data for my analyses. Because of the variations in observations, the average weekly data cannot compare directly to one another. To do this I need the regression models to test the data in their correct timespan.

6.3 Factor data

The factor models introduced in section *5.1 Ordinary Least Square*, requires data on their respective risk factors. In this section I will provide an explanation of the chosen risk factors and their legitimacy. All the chosen factor models require data on risk-free rate and market return. The 3-factor and 4-factor also requires data on SMB and HML. At last, the 4-factor require data on UMD.

6.3.1 Risk-free rate & Market return

AQR provides factor data for almost every stock exchange in the world, including Norway (AQR Capital Management, 2022). But the risk-free rate provided in their dataset, use the U.S.

treasury bill rates as the foundation. Many previous analyses of the Norwegian market have used factors provided by Bernt Arne Ødegaard. His risk-free rate was based on the NIBOR (Norwegian Interbank Offered Rate). Unfortunately, this rate was replaced in 2020 with NOWA (Norwegian Overnight Weighted Average), making his factors outdated. Norges Bank (2020) claims that NOWA is viewed as a nearly risk-free rate, which is why I choose this as the risk-free rate in my thesis.

The risk-free rate is supposed to illustrate the theoretical returns from an investment with zero risk, but NOWA provides a few periods with negative rates. Real life examples of risk-free rate could be returns from government bonds. But if returns were negative, you would rather protect your money by putting it in the bank. The central bank's key policy rate on the other hand is never negative, and NOWA has followed this rate closely over time (Norges Bank, 2020). Therefore, the negative periods in NOWA will be replaced with the key policy rate. Both NOWA and the key policy rate are retrieved from Norges Bank's rate statistics (Norges Bank, 2022).

The market return provided by AQR does not explain what index was used for the construction. Therefore, I rather choose to construct a new market return using indices data from Thomas Reuters Refinitiv Eikon, in addition to the risk-free rate. For an analysis focusing on Norwegian fund managers, the following options for indices are most fitting:

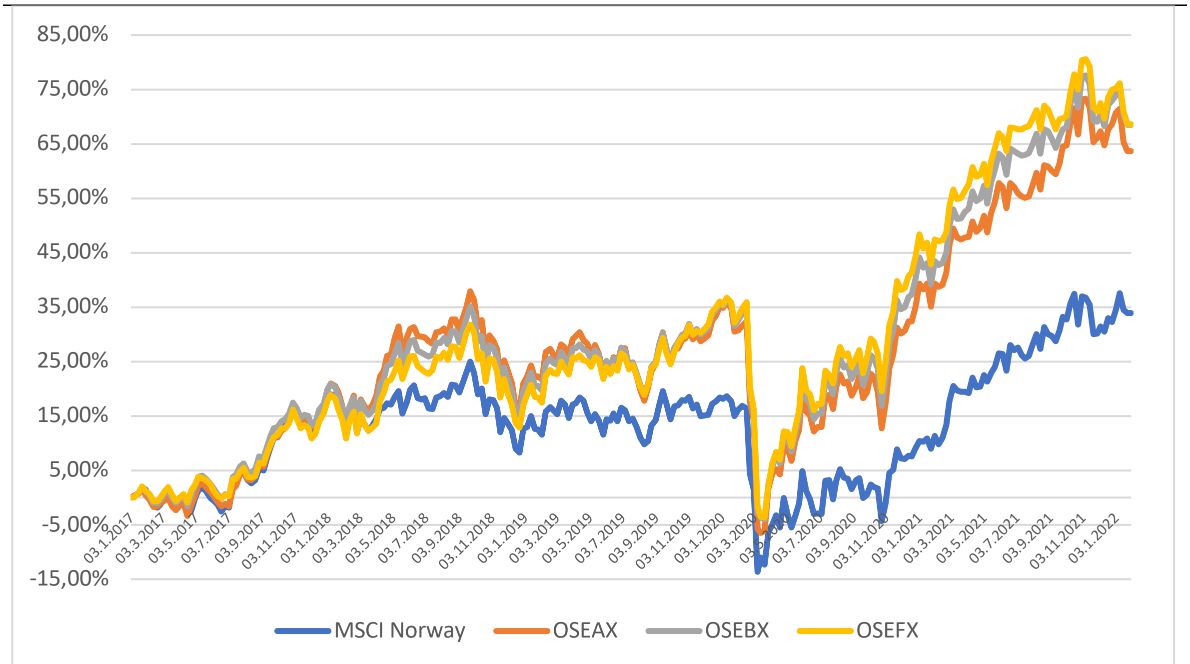
OSEAX	An index representing all listed stocks on Oslo stock exchange. The stocks are adjusted for dividends.
OSEBX	The main index, represented by a selection of the most traded stocks at the Oslo stock exchange. The stocks are adjusted for dividends and reallocated in the index every six months.
OSEFX	The fund index of Oslo stock exchange. Differently to OSEBX, OSEFX is "capped" to comply with UCITS regulations.
MSCI-Norway	An index representing the performance of large- and mid-cap segments on Oslo stock exchange, a total of 12 constituents.

The most fitting benchmark for this thesis would not be restricted to a small number of assets, on the other hand a too broad exposure will also reduce the performance. OSEBX and OSEFX would thus be most fitting. The restrictions OSEFX faces to comply with UCITS, states the following (Oslo Børs, 2017):

> *The market value of securities issued by the same body may not exceed 10% of the index total market value. The market value of securities issued by the same body exceeding 5% index weight must not combined exceed 40% of the index' total market value.*

Of the mutual funds included in my data sample, the majority used OSEFX as their benchmark. Cremers & Petajisto (2009) used a selection process for a benchmark index, by choosing the one with the lowest active share[3]. In this thesis I have used R^2 as my active measurement, and the lowest activity is found with the highest R^2. Among the indices, OSEFX provides me with the highest R^2.

Figure 5: Historic returns of benchmark indices



The figure presents the historic weekly returns for all benchmark indices over the sample period.

To create a "fair" environment for the analyses, I also want to exclude indices with very low returns. Low returns in benchmark will create misleading results, for example that almost all fund managers constantly overperforms. From Figure 5 above, OSEBX and OSEFX are the ones with the highest returns.

[3] Cremers & Petajisto (2009) believed that an index with the greatest amount of overlap with the stockholdings of a fund, is the best fit as a benchmark. A fund manager could pick a benchmark in the sole intention to provide misleading results of beating the market.

As I find that most fund managers have selected OSEFX, as it provides me with the highest R^2, and that it measures up in performance, I find it to be a "fair" choice. OSEFX is thus my chosen benchmark index. Finally, the market return (MKT-RF) is constructed by OSEFX subtracted by the risk-free rate.

6.3.2 Risk factors

For the remaining risk factors, I was able to use the provided data from AQR. SMB (Small minus big), the size factor, is defined as the difference between returns of a portfolio based on small-cap stocks and a portfolio based on big-cap stocks (Fama & French, 1993). HML (High minus low), the value factor, is defined as the difference between returns of a portfolio based on stocks with high book-to-market and a portfolio based on stocks with low book-to-market. UMD (Up minus down), the momentum factor, is defined as the difference between previous equal-weight average high performing stocks minus previous equal-weight average low performing stocks (Carhart, 1997).

6.3.3 Descriptive statistics – factors

In Table 1 below, I present the descriptive statistics on all the risk factors utilized in my regression models. As mentioned in the end of subsection *6.3.1 Risk-free rate & Market return,* the market return (MKT-RF) is constructed using the weekly returns of OSEFX subtracted by the weekly risk-free rate. OSEFX was available in weekly data, but the other factors needed conversion to fit the analyses. The risk-free rate, size factor (SMB), value factor (HML) and momentum factor (UMD) were only available in daily data. In my analyses a conversion to weekly data was therefore necessary.

Table 1: Descriptive statistics on weekly factor data for the sample period

Factors	**Obs**	**Weekly Average Return**	**Weekly Standard Deviation**	**Min**	**Max**
MKT-RF	259	0.22 %	2.25 %	-15.47 %	6.73 %
SMB	259	-0.12 %	1.39 %	-4.02 %	5.79 %
HML	259	-0.04 %	2.42 %	-6.95 %	7.54 %
UMD	259	0.30 %	2.58 %	-13.05 %	8.54 %

The table presents the descriptive statistics for all risk factors. All numbers are derived from weekly data for the total sample period.

From Table 1, I find that on average investors require 0.22% weekly market risk premium. During the sample period, the size factor indicates that portfolios with large-cap stocks perform better than portfolios with small-cap stocks. As for the value factor, it indicates that portfolios based on growth stocks perform slightly better than portfolios with value stocks. However, this factor premium is relatively close to zero. Finally, the momentum factor provides a positive weekly return of 0.30%. These data should not be interpreted in depth for now. But later in the regression models, I will find answers whether the mutual funds returns are weighted to these factors. Then I can discuss if the returns can be explained by these risk factors.

6.4 Fulfilling OLS assumptions

To ensure validity of my regression models, I will explain the methods used to fulfill the assumptions introduced in section *5.2 OLS assumptions*. And further, how to correct potential flaws within the assumptions. I want to repeat the assumptions for this section. The regression model must be linear, the mean of the error term must be zero, all explanatory variables are uncorrelated with the error term, no autocorrelation, no heteroskedasticity, no multicollinearity and a normally distributed error term. I will begin testing the latter because this one is termed optional and usually have less impact on the results of the analysis. In *Appendix 3* and *Appendix 4*, I explain more thoroughly how all assumptions are fulfilled, completed with a list of the remaining models results.

6.4.1 Assumption of normally distributed error term

Normally distributed error terms will be tested using a joint test for skewness and kurtosis in STATA. If the results in the data lead to indication of error terms not to be normally distributed, I will not regard this as a big problem. When conducting OLS-models, one can use the Gauss-Markov theorem, which excludes this 7th assumption. It states in short form that assumptions are met when “OLS is BLUE”, where BLUE stands for “Best (meaning minimum variance) Linear Unbiased Estimator” (Studenmund, 2019, p. 124). If the 7th assumption on the other hand is met, then this would only strengthen the Gauss-Markov theorem. With a 5% significance level, I found that 35% of the funds had models with significant normality. This means that the majority of 65%, did not have normally distributed error terms.

6.4.2 Assumption of no autocorrelation

Timeseries data have a natural tendency of autocorrelation, caused by events taken place in a previous time-period (Studenmund, 2019, p. 293). This claim would especially impact data based on indices. To test for autocorrelation, I used the Lagrange Multiplier test (Breusch-Godfrey LM test) in STATA. With a 5% significance level, I find that 90% of the funds regression models resulted in non-significant autocorrelation, while 10% in fact were significant. This can be corrected by using a robust Newey-West estimation. Instead of using standard errors the Newey-West rather use corrected standard errors which produces lower t-scores (Studenmund, 2019, p. 313). This decreases the probability of coefficients to be significantly different from zero.

6.4.3 Assumption of no heteroskedasticity

I used the White-test in STATA to check if my regression models fulfilled this assumption. With a 5% significance level, the results were that only 44% of the funds regression models provided p-values indicating homoskedasticity. The majority of 56% resulted in p-values indicating that there in fact are heteroskedasticity. As with the autocorrelation, I can counter this using the corrected standard errors with the robust Newey-West estimation (Studenmund, 2019, p. 339).

6.4.4 Assumption of no multicollinearity

Multicollinearity is usually a problem when regression models have strongly correlated explanatory variables. P-values which in normal circumstances are significant, can be impacted to display non-significant explanatory variables. It can often be a problem if the data sample has a low number of observations. To test for multicollinearity, I just needed to create and interpret a correlation matrix between the explanatory variables. Correlation coefficients between the explanatory variables of + – 0.5 or lower, indicates that the model is not affected by multicollinearity.

Table 2: Correlation matrix

	MKT-RF	*SMB*	*HML*	*UMD*
MKT-RF	1			
SMB	-0.1155183	1		
HML	0.25683416	-0.347701	1	
UMD	-0.3566099	0.25709339	-0.3782754	1

From the correlation matrix above in Table 2, I find that all explanatory variables have a relatively low correlation between each other. The correlation matrix thus indicates that there is no problem with multicollinearity.

To be certain about the outcome above, I also test for multicollinearity using the VIF-index. A VIF-index close to 1, indicates no problems with multicollinearity, but over 5 do indicate a problem.

Table 3: VIF-indices

Variable	VIF	1/VIF
MKT-RF	1.30	0.768908
SMB	1.29	0.774437
HML	1.17	0.855316
UMD	1.16	0.860541
Mean VIF	1.23	

From the VIF-indices in Table 3, I find the same results as from the correlation matrix. All the explanatory variables provide VIF-indices close to 1, confirming that there is no problem with multicollinearity.

7. Results and discussion

In this chapter I will present all empirical results from my tests. The results will be compared and discussed. I will begin with determining which model that fits my analyses best. To answer my first research question, I will evaluate the performance of all funds compared to level of activity, years of experience and level of risk. For my second research question, I will examine how the performance and risk level varies for the two market conditions. Finally, to understand whether fund managers are truly great stock pickers or have "timing ability", I need to test the robustness of the models.

7.1 Fit of regression models

In this thesis I want to select the model that explains the results in the best manner. I want to select the regression model which has the best fit towards the factors included. The more factors a regression models utilize, the more they tend to provide insignificant results. To be as precise as possible, I therefore check which models are most fitting.

Table 4: Results from equal-weighted mutual fund portfolio

Models	**α**	**MKT-RF**	**SMB**	**HML**	**UMD**	**R^2**
Single-factor	0.39%	0.896				0.962
	(0.778)	(0.000)				
3-factor	1.37%	0.899	0.152	0.026		0.971
	(0.217)	(0.000)	(0.000)	(0.013)		
4-factor	0.99%	0.905	0.147	0.031	0.018	0.971
	(0.381)	(0.000)	(0.000)	(0.003)	(0.094)	

Results from three equal-weighted portfolios of all mutual funds. Alphas are annualized. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. R^2 is retrieved from the regression models of the equal-weight portfolios. Coefficients are presented for each factor, with their respective p-value in parenthesis beneath.

In Table 4, I introduce an equal-weighted portfolio based on all mutual funds. This portfolio is then tested on the three types of regression models. The 4-factor model provide similar results to the 3-factor, except that the UMD factor is not significant at the 5% significance level. The 3-factor alpha is higher than the 4-factor, while also the p-value for the 3-factor alpha is closer to being significant. Additionally, they both have the same explanatory power. Since the rest of the risk-factors are significant, I assume that the UMD-factor is not utilized by the fund managers in Norway. Meaning that fund managers are not exposing their funds towards this factor. This makes the UMD-factor, and thus the 4-factor model irrelevant. Moving forward I will continue with the most fitting model for my analyses, which here is the 3-factor model.

Interestingly, when using the equal-weighted portfolio, I find that the R^2 is just above 0.97 which is my chosen limit for "closet-indexers". This indicates that mutual funds on average during the whole sample period are potential "closet-indexers". Since R^2 is not the most precise tool for this purpose, I want to compare this to the R^2 of true index funds.

Table 5: Results from equal-weighted index portfolio

Models	α	MKT-RF	SMB	HML	R^2
3-factor	-0.09%	0.978	-0.075	0.036	0.989
	(0.898)	(0.000)	(0.000)	(0.000)	

Results from an equal-weighted portfolio of all index funds. Alpha is annualized. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. R^2 is retrieved from the regression model of the equal-weight index-portfolio. Coefficients are presented for each factor, with their respective p-value in parenthesis beneath.

Table 5 presents the results of the 3-factor regression model from an equal-weighted portfolio of all index funds. Not surprisingly, the index fund portfolio performs close to zero, and worse than the outcome for the mutual fund portfolio. As expected, the R^2 is close to 1. From Table 4, I found that mutual funds on average are "closet-indexers" with an R^2 of 0.971. This is not far from the R^2 of index funds at 0.989. But still far enough that I can tell apart true index funds from potential "closet-indexers". I still want to utilize the limit of 0.97, since I expect mutual funds to be even more differently allocated than index funds and yet perform well.

7.2 How does fund manager activity, experience and risk impact performance?

In this section I will start with summarizing the most important findings of all the individual regressions, to separate those funds which are potential "closet-indexers" from those who are more actively managed. This way I can test how the performance varies between the groups. In *Appendix 5* there is presented a complete list of all individual regressions. To complete this section, I will examine how years of experience impact the performance of mutual funds, and finally compare the Sharpe Ratios to get an understanding for the risk involved.

7.2.1 Summary of individual regressions

Almost all mutual funds have statistically significant MKT-RF coefficients at the 1% significance level. There are only two exceptions, "KLP Obligasjon 1 Ar Mer Samf.Ansvar" which is significant at 10% level, and "KLP Natid Mer Samfunnsansvar" which is insignificant.

For the SMB factor 77% of the funds are significant, and for HML about half of the funds are significant. All alpha values are presented on an annualized basis. Overall, I find that 76% of the mutual funds have a positive alpha, while 19% of all funds are significantly positive. This finding is in direct opposition of Eugene Fama´s (1970) efficient market hypothesis. There are mutual funds that overperform the Norwegian market, though only a minority. Grossman and Stiglitz' (1980) reflections about inclusion of information compensations in the market equilibrium, seems more valid. That since some fund managers overperform, they need to be good stock- or market analysts. I must emphasize that at this point in the thesis I have yet to include the mutual fund fees.

All mutual funds with significant alphas are highlighted in the table in *Appendix 5*. The best performing fund is "Storebrand Fremtid 80 A" with a significant alpha of 12.69%. On the opposite I can only find one mutual fund with a significantly negative benchmark-adjusted performance, "Eika Norge", with an alpha of -2.06%. Besides that, "Storebrand Vekst N" provides the worst insignificant result at -6.54%.

To cross examine these results, I also created a table with the annualized Sharpe Ratios of all mutual funds in *Appendix 6*. "Alfred Berg Gambak N" is the one with the highest Sharpe Ratio of 1.67, which is recognized as only an "Acceptable" Sharpe Ratio. None of the mutual funds have "Good" or "Excellent" Sharpe Ratios. In total I find 18 of the mutual funds with "Acceptable" Sharpe Ratio, which all are highlighted in the table in *Appendix 6*. 10 out of these 18 mutual funds are also among the 16 mutual funds with significant positive alphas. This is evidence that these funds are overperforming while also managing to have a decent risk exposure. On the negative side I find two mutual funds with negative Sharpe Ratios, "KLP Natid Mer Samfunnsansvar" with -0.77 and "XACT Derivat Bear" at -1.72. The latter was merged as early as in 2017. As seen in the previous chapter in Figure 5, the market was generally performing well that year. For such a period it is not unexpected that an ETF based on "bear-market" derivates, would yield any other way than with negative risk adjusted performance.

7.2.2 Performance by activity levels

From the table of all the individual regressions in *Appendix 5*, I have also the opportunity to examine the level of activity for each mutual fund. Earlier in Table 4, I found that mutual funds on average are potential "closet-indexers". Now I find that the majority in fact are more active. In Table 6 I have summarized and ranked the regression results, while also combining the mutual funds Sharpe Ratio from *Appendix 6*, and years of experience from *Appendix 1*.

Table 6: Summary of mutual funds ranked by activity

Ranked mutual funds	Annualized α	R^2	Annualized Sharpe Ratio	Years of experience
10 most active				
KLP Natid Mer Samfunnsansvar	0.52%	0.093	-0.77	1.3
KLP Obligasjon 1 Ar Mer Samf.Ansvar	1.05%	0.134	1.41	2.3
Vibrand Kreditt	3.17%	0.208	0.73	4
KLP Kort Horisont Mer Samfunnsansvar	2.10%	0.341	0.73	1.3
DNB 2020	1.05%	0.498	1.02	5.5
Heimdal Jorde	3.71%	0.523	0.82	2.5
KLP Lang Horisont Mer Samfunnsansvar	9.80%**	0.567	1.40	1.3
Landkreditt Norden Utbytte A	6.43%	0.576	0.87	3
DNB Spare 100	8.67%*	0.577	1.18	3
Storebrand Fremtid 80 N	12.11%**	0.577	1.44	1.1
3 least active				
Eika Norge	-2.06%*	0.956	0.50	2.5
C WorldWide Norge	-2.06%	0.959	0.59	3
Sbanken Framgang Sammen	-0.52%	0.961	0.65	6
"Closet-indexers"				
Alfred Berg Norge [Classic]	0.52%	0.970	0.75	11.5
KLP AksjeNorge	-0.52%	0.971	0.62	9.1
DNB Norge N	0.52%	0.972	0.59	15.5
PLUSS Markedsverdi	-2.06%	0.973	0.55	27
DNB Norge R	-2.06%	0.973	0.51	15.5
Storebrand Norge I	0.52%	0.974	0.77	17.5
DNB Norge A	-1.03%	0.978	0.71	15.5

*The table summarizes the alphas and R^2 from 3-factor regressions in ranked activity level, with mutual funds Sharpe Ratio and experience. The "closet-indexers" were identified based on the earlier defining limit of 0.97 for R^2. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. Significance is illustrated with p-values: *p < 0.1, **p < 0.05, ***p < 0.01*

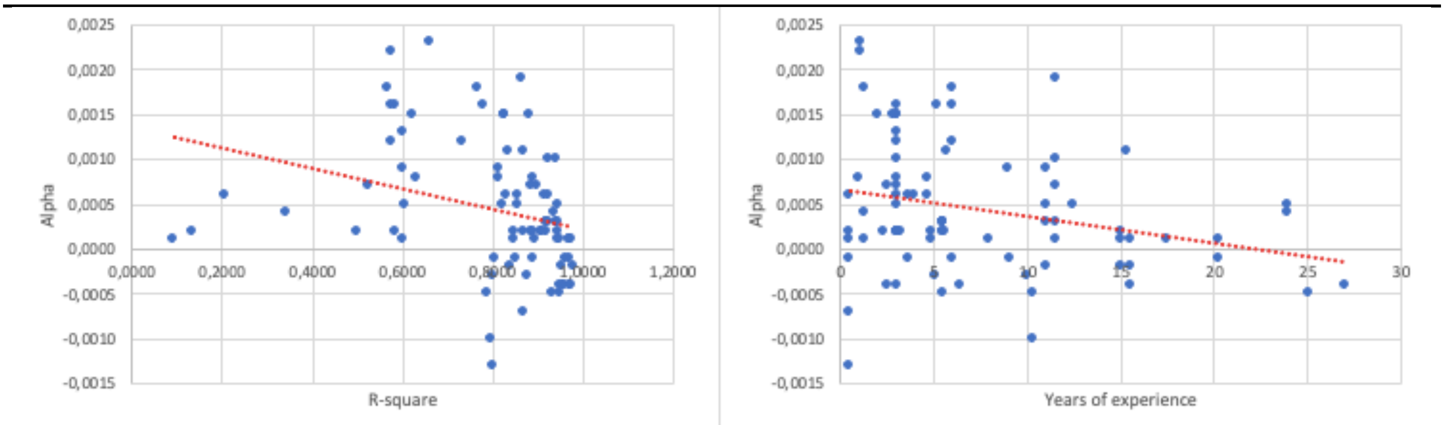
I chose in this summary to only highlight the mutual funds in groups of 10 most active and 10 least active. Because 7 of the 10 least active had an R^2 above 0.97, I rather split this group in two: 3 least active and "Closet-indexers". Although most results are insignificant, the idea is to illustrate how the performance varies in line with the level of activity.

The most actively managed funds clearly provide better performance than those of the least active funds. Three of these funds also have significantly positive alphas. The Sharpe Ratio also indicates that the most active performs better. The three funds with significant positive alphas actually provide "Acceptable" Sharpe Ratios. In addition to this, I find that "DNB 2020" and

"KLP Obligasjon 1 Ar Mer Samf.Ansvar" have "Acceptable" Sharpe Ratios. The rest of the most active funds are according to their "Bad" Sharpe Ratio, too much exposed to risky assets compared to their actual returns. For the least active funds on the other hand, most of them provide negative alphas. But I only find "Eika Norge" with significantly negative alpha. The Sharpe Ratios of all least active funds are also termed "Bad", as these are clearly not yielding high enough returns to compensate for the individual risky assets within the funds.

Finally, what I believed was the most important task of Table 6 was to separate the mutual funds that crossed the R^2 limit of 0.97. This group is what I define as potential "closet-indexers", which all have poor benchmark-adjusted performance. Interestingly all fund managers in these funds have long experience compared to the more active funds. Additionally, I find that even the defined "closet-indexers" are a bit more active than the equal weighted index-portfolio in Table 5. This won't change the fact that the performance of the "closet-indexers" are zero to none. Especially considering that these results are based on gross returns.

Figure 6: Scatterplot of R^2 and experience compared to alpha



Scatterplots created using years of experience and R^2, against the alpha from 3-factor regressions for all mutual funds.

In Figure 6, I present two scatterplots. One comparing alpha with R^2, and the second one comparing alpha with years of experience in the fund. In the two plots, there are also drawn linear trend lines. In the one to the left I find indication of more activity within the funds (lower R^2), results in better performance. Especially if I were to remove some of the outliers with extremely low R^2. These extreme R^2 incidents could be due to the low observations of the funds (see *Appendix 2*). Another possibility is that those funds with the highest activity level are not at all fit with the 3-factor model. Amongst the ten most active funds in Table 6, seven are mixed-assets funds and could for example be too much weighted towards interest rate investments. However, they could be viewed as truly more active, as they invest in multiple asset classes.

In the second scatterplot in Figure 6 to the right, I find similarities with Costa et al. (2006) about years of experience and performance. Fund managers with less experience perform better. There are of course many outliers of low experience with low performance. But overall, there is a trend for better performance by fund managers with lower experience. Again, I need to emphasize that the data of yearly experience only accounts for years within the respective fund. But one could argue that no funds are alike, and it demands persistence to perform with the selected strategy. Anyhow it seems that strategies for shorter timespan have performed better.

7.2.3 Performance by experience levels

With these two observations in mind, I want to dig deeper into how results of the mutual funds vary when performed during calm- and risky-markets. More specifically, to investigate how this impacts the performance of the selected experience groups. To begin with I have split the mutual funds into three groups of experience-levels: "Up to 3 years", "Between 3.1 and 8 years", and "Above 8 years". Before embarking on the results of each subperiod, I need to understand how the different experience groups perform overall. I will start with a 3-factor regression for the total sample period with equal-weighted portfolios of the experience groups.

Table 7: Equal-weight portfolios of experience levels

Experience levels	α	MKT-RF	SMB	HML	R^2
Low	1.23%	0.824***	0.144***	0.009	0.938
Medium	2.29%	0.877***	0.209***	0.017	0.941
High	0.75%	0.993***	0.117***	0.057***	0.977

*Results from equal-weighted portfolio based on experience level for the total sample period. Alphas are annualized. R^2 is retrieved from the regression models of the equal-weight portfolios. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. Significance is illustrated with p-values: *p < 0.1, **p < 0.05, ***p < 0.01*

The overall results from Table 7, indicates that all fund managers during the total sample period outperform the market. Especially those with experience from 3 to 8 years perform best with an alpha of 2.29%, followed by the youngest experienced fund managers with an alpha of 1.23%. But the alphas are insignificant, meaning that I cannot claim anything concrete about these results. I also find that the high-experienced group are more exposed towards the market and less towards the SMB factor, compared to the other groups. Meaning that high-experienced fund managers weight their funds more in line with the benchmark index and have a lower conviction on potential small-cap stocks to overperform large-cap stocks. They are also slightly more weighted towards the HML factor. But this conviction for value stocks to overperform is very low for all groups, so I assume that this is not essential for the performance.

All factor-loadings for the high-experienced group have more similarities with the equal-weight index portfolio in Table 5. This can be reflected in the activity levels as well. The high-experienced group is the only one to exceed the limit for potential "closet-indexers". In fact, the group is not far from the same level R^2 as the lowest active mutual fund "DNB Norge A". This can possibly be due to the amount of potential "closet-indexers" included in the group. Amongst the 29 mutual funds in the high-experienced group, I find all 7 of the "Closet-indexers". The least experienced fund managers are the most active managers, but only just so with an R^2 of 0.938 compared to the medium experienced group with an R^2 of 0.941.

It seems that more activity and less experience contribute to better performance. But due to the insignificant alphas, it cannot be concluded at this stage. Numbers from individual mutual funds in Table 6 also gave indications that the most active and youngest perform best, at the same time it also displayed big variety in performance for the least experienced managers. This was better illustrated in Figure 6, where the outliers are visible. When comparing the scatterplots with the results of Table 7, it also seems that those who perform better are more active, but not the most active. And that they are less experienced, but not the least experienced fund managers.

7.2.4 Evaluating risk

"Boring is the new exiting" was a statement from a chief economist and strategist in Pareto Asset Management (Bergh, 2021). It was based on a portfolio of stocks with the lowest market beta, that had overperformed on Oslo stock exchange since year 2000. Looking at the two least-experienced groups above in Table 7, the market beta is lower than the equal-weighted index portfolio in Table 5. This could indicate that these portfolios are less risky, but their Sharpe Ratios tells a different story.

Table 8: Sharpe Ratio by experience level

Experience levels	Sharpe Ratio
Low	0.65
Medium	0.70
High	0.64

The table presents annualized Sharpe Ratios for equal-weighted portfolios of the different experience levels.

From Table 8, it is very clear that the risk-level for all asset holdings of the funds exceed the return they should generate. All groups of fund managers provide on average "Bad" Sharpe Ratios. Looking beyond the insignificance in Table 7, the medium-experienced group perform best. In *Appendix 6*, I can only find three mutual funds from this group with “Acceptable” Sharpe Ratios. “Handelsbanken Norge (NOK)” with 1.03, “DNB Lev Mer – 2070” with 1.37, and “DNB 2020” with 1.02. This is clearly not enough to claim that historic higher return results in lower risk, as previous studies like Grønsund & Lunde (2010) concluded.

So, is boring really the new exiting? The Sharpe Ratio sure does not give indication that these funds provide low enough risk in regards of the return. This problem may of course be due to the major changes in market volatility playing out for the duration of the total sample period.

7.3 What implications will variations in market conditions have on this?

At this point I have identified how both the performance and risk level is affected by activity and experience. To answer my second research question, I need to examine how the results will alter with the different market conditions. I will again assess the performance, activity, experience and risk level.

7.3.1 Impact of volatility

To further examine how the performance of these groups vary during different levels of market risk, I have split the sample period in two. One period representing a low-risk market, where the VIX-index is less than 20%. The second period representing a high-risk market, where the VIX is above 20%. In the same manner as the regression above, the same equal-weighted portfolios of experience groups will now be tested for the mentioned periods.

Table 9: Experience levels based on VIX

Experience levels	α	MKT-RF	SMB	HML	R^2
VIX < 20%					
Low	0.23%	0.899***	0.129***	0.025	0.914
Medium	1.92%	0.775***	0.130***	0.028**	0.913
High	0.26%	0.930***	0.082***	0.046***	0.950
VIX > 20%					
Low	0.06%	0.792***	0.191***	-0.007	0.957
Medium	7.47%*	0.912***	0.262***	0.016	0.957
High	4.49%*	1.017***	0.133***	0.071***	0.988

*Results from equal-weighted portfolio based on experience level. All three experience groups are tested for two periods of different volatility levels. Alphas are annualized. R^2 is retrieved from the regression models of the equal-weight portfolios. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. Significance is illustrated with p-values: *p < 0.1, **p < 0.05, ***p < 0.01*

The first point to highlight from Table 9, is that mutual fund performance is clearly better during high-risk markets. When the VIX is above 20%, both the medium- and high experienced groups have positive significant alphas of respectively 7.47% and 4.49%. The only group performing better during low-risk market is the group of low-experienced fund managers, but this is insignificant and cannot be used to explain the differences in market conditions. As all three groups are created by equal-weight portfolios, they all have the same number of observations for the total period. But the subperiods have different observations. During the low-risk market I find 183 observations, while only 76 observations for the high-risk market. Since the high-risk market provides significant alphas with less observations, the number of observations should not matter for the results during the low-risk market. This justifies that both the high-experienced- and medium-experienced fund managers significantly outperforms both the benchmark index and the low-experienced fund managers during high volatility.

Both the results of Bessembinder et al. (2019) and Norang & Agustsson (2018) implied that an investor must be skilled to take part of the excess value created in the stock market. This seems to be true for this data sample as well, where only some of the fund managers have been able to significantly overperform during high-risk markets. But instead of the youngest experienced fund managers like the results of Costa et al. (2006), I rather find that it is the fund managers with 3 to 8 years of experience that perform best.

When examining the activity levels for these groups, I still find that lower experienced funds are more active. But during the low-risk period all groups, and even the high-experienced fund managers provide an R^2 lower than 0.97, indicating that all funds increase their activity during less volatile periods. Keep in mind that the high-experienced fund managers still include all seven of the potential “closet-indexers”. This can potentially explain why this group still have the highest R^2 at 0.95. When the market on the other hand involves more risk, the results show similarities to the more recent study of Petajisto (2018), that the level of active management reduced for all groups. Now the two least experienced groups have increased their R^2 up to 0.957, and the highest experience group are back to potential “closet-indexing” with an R^2 of 0.988. As the best performing medium-experienced fund managers consists of the more active funds in both periods, the results are in line with Amihud & Goyenko (2013), who also found that the more active funds performed better using R^2 as the active measurement.

The change in activity within the funds from low-risk- to high-risk periods, can partly be explained by the change in factor bets. The fund managers with experience above 3 years, increase their factor bets towards the market (MKT-RF). At the same time, all fund managers increase their factor bets on small-cap stocks (SMB). The previous state was that more of the funds asset's variation were explained by other risk factors than those included in the model, i.e. more active. With less activity, the R^2 increased, meaning that the remaining unknown factor bets decreased. More of the performance are explained by the 3-factor model. As the market index is considered a safer bet, I assume that some of the fund managers tries to reduce their overall risk with the move towards a heavier weight-allocation to the market. And with the increased conviction on small-cap stocks, all of them try to exploit more of the small-cap stocks tendency of overperforming in the long-run. Regarding the factor bet on value-stocks (HML), I find similar results as for the total period in Table 7. The high-experienced group have the highest conviction, but overall the factor bets are fairly low.

The medium-experienced group of fund managers positioned their funds even higher towards small-cap stocks, which could attribute to why they outperform both the benchmark index and the other groups of fund managers. As both the medium- and high-experienced fund managers increased their performance with this move, it seems experience can result in better abilities to predict market conditions or undervalued sectors. But with the even higher conviction on small cap-stocks and more activity within unknown factor bets, the medium-experienced group also outperform the high-experienced group. Too much experience can result in a fund manager to be too comfortable in the routines, they may get too risk averse and lose out on opportunities for higher returns.

7.3.2 Changes in Sharpe Ratio

Looking at risk regarding beta as in subsection *7.2.4 Evaluating risk*, the market beta for the low-risk market is lower than for the high-risk market. This contradicts what I previously mentioned about reducing risk with increased volatility. But looking at the beta alone is not quite correct. The R^2 shows that more of the model's variation is explained by the factors in high-risk markets. This means that during low-risk markets there are more unknown factors with unknown betas. This is risk not accounted for. I therefore assume that during a high-risk market it is natural to reduce the risk-exposure, by rather placing larger portions of investments in safer bets. And the benchmark index tracks more of the safer stock investment on the exchange, thus reducing risk. But I also need to point out that more experienced fund managers diversify from the benchmark index with increased risk towards small-cap stocks.

Table 10: Sharpe Ratios for subperiods

	Sharpe Ratio	
Experience levels	**VIX < 20%**	**VIX > 20%**
Low	1.71	-0.41
Medium	1.89	-0.10
High	1.74	-0.21
Index-fund	1.78	-0.32

The table presents annualized Sharpe Ratios for equal-weighted portfolios of the different experience levels and the different market conditions. "Index-fund" is created with an equal-weighted portfolio of all index funds.

To better understand the risk-preferences for the experience groups, I shall examine the results of the Sharpe Ratios in Table 10. Here they provide completely different results than the regressions. I rather find that all groups of experiences provide "Acceptable" Sharpe Ratios during periods of less volatility. While they all provide "Bad" Sharpe Ratios during high volatility. The Sharpe Ratio explains that the funds perform better during the low volatile periods, due to the lower risk involved in the asset allocations.

The sudden "bear-market", when the pandemic hit in February 2020, may have influenced the Sharpe Ratios too much. The period was naturally burdened by negative returns, which directly results in negative Sharpe Ratios. This is especially reflected when considering that the index-fund portfolio provided an even worse Sharpe Ratio than the medium- and high-experienced fund managers. All funds, including index funds, suffered huge losses during parts of the period. Some of these losses were covered when the market switched back to "bull-market", but the majority was earned outside of the most volatile periods.

Because of the negative Sharpe Ratios in the high-risk market, it cannot be used to explain any degree of risk-adjusted performance. But it does provide insight to the difference between risk-levels of mutual funds compared to index funds. As the index funds has worse Sharpe Ratio than the more experienced fund managers, I find that their mutual funds are capable of positioning better when volatility occurs. The adjustments both limits their losses and creates an advantage for the coming "bull-market". The medium-experienced fund managers have the best Sharpe Ratio during both periods, indicating more risk aversion. As they also have the best significant overperformance, I find evidence for timing ability when the market condition changes.

7.4 Robustness test

Will the results for the medium-experienced funds persist when the least- and most-experienced funds within are changed to different groups? The changes in experience groups, resulted in three funds with manager-experience of 3 years were moved to the low-experience group: "Eika Spar", "FORTE Tronder" and "FORTE Norge". And one fund, "Eika Balansert", with manager-experience of 8 years was moved up to the high-experience group.

Below in Table 11, I test the robustness of the experience levels within the new groups. All periods provide similar results to the original tests from Table 7 and Table 9. The alphas are still showing that the medium-experienced group perform best, but now it performs even better. As before, it is still only the medium- and high-experienced groups that provide significant alphas during high volatility. The factor loadings are relatively similar, also when accounting for the degree of significance. The biggest change is that the medium-experienced group now are more actively managed than all the other groups during all sample periods.

Table 11: Robustness test for new groups

Experience levels	α	MKT-RF	SMB	HML	R^2
Overall period					
Low	1.40%	0.840***	0.152***	0.013	0.950
Medium	2.55%	0.890***	0.219***	0.009	0.930
High	0.74%	0.971***	0.116***	0.054***	0.977
VIX < 20%					
Low	0.38%	0.899***	0.132***	0.022	0.922
Medium	2.28%	0.772***	0.131***	0.026*	0.900
High	0.27%	0.907***	0.081***	0.046***	0.950
VIX > 20%					
Low	0.83%	0.814***	0.199***	0.004	0.966
Medium	8.31%*	0.931***	0.275***	0.003	0.950
High	4.46%*	0.995***	0.132***	0.067***	0.988

*Results from equal-weighted portfolio based on experience level. All three experience groups are tested for two periods of different volatility levels as well as the whole period. Alphas are annualized. R^2 is retrieved from the regression models of the equal-weight portfolios. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. Significance is illustrated with p-values: *p < 0.1, **p < 0.05, ***p < 0.01*

These minor changes indicate robustness of the results. There is evidence that the medium-experienced group of funds significantly outperforms the benchmark and the other groups of experience-levels when the volatility is above 20%.

7.5 Accounting for mutual fund expenses

Until now, all results have been retrieved from models where the mutual fund expenses have been excluded. To see whether the same groups still overperform using the net returns, I rerun the regressions from Table 9. But now the average mutual fund expense of 1.19% is subtracted from the excess return. The data on individual performance fee is available for some mutual funds, but specifically when these fees occur is not available. Therefore, performance fee is still not included.

Table 12: Experience levels based on VIX (Net returns)

Experience levels	α	MKT-RF	SMB	HML	R^2
VIX < 20%					
Low	-0.97%	0.899***	0.129***	0.025	0.914
Medium	0.71%	0.775***	0.130***	0.028**	0.913
High	-0.94%	0.930***	0.082***	0.046***	0.950
VIX > 20%					
Low	-1.13%	0.792***	0.191***	-0.007	0.957
Medium	6.19%	0.912***	0.262***	0.016	0.957
High	3.25%	1.017***	0.133***	0.071***	0.988

*Results from equal-weighted portfolio including the average fund expenses, based on experience level. All three experience groups are tested for two periods of different volatility levels. Alphas are annualized. R^2 is retrieved from the regression models of the equal-weight portfolios. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. Significance is illustrated with p-values: *p < 0.1, **p < 0.05, ***p < 0.01*

All beta coefficients for the risk factors in Table 12 are identical to the originals in Table 9, when using the gross returns. They are also equally significant at the same significance levels, except for all the alphas which now are insignificant. The R^2 also have the same values as previously.

The results of performance are still similarly ranked as in Table 9, and thus the medium experienced fund managers are performing best during both low-risk- and high-risk markets. But as these results are insignificant, I cannot conclude that this group of mutual funds, or any other for that matter, are performing better when taking account for the mutual fund expenses.

7.6 Summary of results

From the summary of individual regressions for the overall period in section *7.2*, I find that 16 of the mutual funds have significantly positive alphas. This is clear evidence that some mutual funds beat the Norwegian market, which contradicts Fama's (1970) efficient market hypothesis. I also find similarities with Costa et. al (2006), that less experienced fund managers perform better. The activity level for the overall period, indicates that less experienced fund managers are more active. I also identify 7 potential "closet-indexers", which all are included in the group of fund managers with high experience.

In section *7.3* I find similar results for the low volatile markets and the total period. But when the markets involve more risk, both the medium- and high-experienced groups of fund managers significantly overperform. This is even more related to Costa et al. (2006). Fund managers recognize volatility and reallocate accordingly, and with this move perform significantly better. But rather than the ones with 1 year experience, it is the fund managers with experience from 3 to 8 year that perform best. This medium-experienced group has the absolute highest significant alpha of 7.47%. This supports the conclusion of Amihud & Goyenko (2013), as the group also consists of the more actively managed ones. For the low-experienced fund managers, I still find poor insignificant results.

Just as Petajisto (2018) found, higher risk in the market leads to reduced activity. As the R^2 increase, both the low- and medium-experienced groups decrease their active positions unexplained by the model. The medium- and high-experienced fund managers also increased their exposure to both the market and small-cap stocks. The Sharpe Ratio indicates the opposite of the 3-factor model. That funds have better risk-adjusted performance during low-risk markets, and worse during high-risk markets. I assume the negative returns during parts of the high-risk markets had too much impact on the Sharpe Ratio. Since both the medium- and high-experienced managers have better Sharpe Ratio than an equal-weighted index portfolio.

The results are robust to changes in experience levels, the medium-experienced group still provide the best results. But when mutual fund expenses are included, all experience groups provide insignificant alphas for both market conditions.

8. Conclusion

The long running debate on active- vs. passive fund management is difficult to find a firm solution to. In the recent years the public's interest in fund has increased tremendously. In addition to boosting the liquidity in funds, this has also increased the competition for the best employees and fund performance. During the same time the world has endured unfortunate incidents causing high volatility in the market. In this thesis I have examined the Norwegian market with the following problem statement: ***Under what circumstances can active fund management in Norway outperform passive investment strategies?***

The few mutual funds that do significantly overperform in the total period, are not recognizable by group characteristics. When the general risk in the market reduces, I find evidence that all mutual funds reduce their risk according to both risk-factor exposure as well as the Sharpe Ratio. All funds also become more active, by increasing their exposure to unknown factor bets. But I cannot find evidence for significant overperformance. With changing market conditions where market risk on the other hand increases, the mutual funds reduce their activity. Most notably the mutual funds with high-experienced fund managers are now replicating index funds very closely. In fact, all potential "closet-indexers" are found within the group of high-experienced fund managers. But even so, both the groups of medium- and high-experienced fund managers do significantly outperform the market. Both reduce their unknown factor bets, but among them the medium-experienced group still have slightly more active positions and thus significantly outperform the other groups as well. Because they still maintain a better risk-level than index funds, I find evidence that mutual funds with medium-experienced fund managers are better stock pickers and have timing ability for changes in market conditions.

For investors in the Norwegian market, one should invest in index funds under normal circumstances. But when volatility gets higher than 20%, investors should sell index funds and buy a group of mutual funds that are more actively managed and has fund managers with experience between 3 to 8 years. Conversely, the evidence disappears when examining the results using net returns, then all groups provide insignificant alphas. Therefore, I cannot claim that mutual funds, for any groups of experience levels, outperform the market. For the investigated circumstances, I conclude that index funds are the better investment choice.

8.1 Limitations

The thesis has of course it's limitations. Among them sample size, which has been limited to equity and mixed assets with both domicile and geographical focus in Norway. These limitations implies that the evidence I find are not generalizable to a larger sample of mutual funds. The information on each fund is also limited by the data available from Thomas Reuters Refinitiv Eikon. A few funds lacked data on certain areas, which limited the complete list of funds I could use. I managed to save some information with the use of Morningstar's public version, but not all. In my thesis the experience level was arguably simplified due to this problem. Because of the quantity of funds and the timespan of the thesis, I was not able to find more detailed data on work experience. It restricted me to only examine the experience within the respective funds, and not the complete work-experience for each fund manager.

8.2 Further research

For a master thesis, time is a limited resource. A study on a smaller sample of funds may allow for a better distribution of time for the tasks ahead. This can help to overcome the limitation on experience levels. If available, one will have more time to retrieve the complete information on fund managers work experience. With more time and less funds to investigate, one could also retrieve fund holding data. It would be interesting to compare results of Active Share, which demands fund holding data, with the results of R^2.

With the evidence of overperformance during high volatility using gross returns, it could also be interesting to examine if there are similar results for other volatile market periods. Possibly a study on different timeframes including the dot-com bubble in 2000 and the financial crisis of 2008. Further research could also study how other markets (preferably bigger) compares to the results of the small Norwegian market.

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Appendices

Appendix 1 – Introduction to sample of all funds

Appendix 2 – Descriptive statistics for all funds

Appendix 3 – The classical assumptions for regression models

Appendix 4 – Tests for OLS assumptions

Appendix 5 – Individual regressions for all mutual funds

Appendix 6 – Sharpe Ratio of all mutual funds

Appendix 1: Introduction to sample of all funds

Mutual funds	Fund TNA in mill USD	Operating Expenses	Years of Experience
Alfred Berg Aktiv	394.47	1.51 %	11.5
Alfred Berg Gambak	1037.24	2.00 %	11.5
Alfred Berg Gambak N	1037.24	1.00 %	11.5
Alfred Berg Humanfond	22.92	1.27 %	11
Alfred Berg Norge DIST	809.08	0.70 %	11.5
Alfred Berg Norge [Classic]	809.08	1.20 %	11.5
C WorldWide Norge	46.29	1.30 %	3
DNB 2020	20.88	0.64 %	5.5
DNB Aktiv 80	705.85	1.25 %	11
DNB Lev Mer - 2070	1.08	0.34 %	5.2
DNB Norge	815.55	1.40 %	5.5
DNB Norge A	1066.49	1.35 %	15.5
DNB Norge N	1066.49	1.00 %	15.5
DNB Norge R	1066.49	0.75 %	15.5
DNB Norge Selektiv A	511.21	1.35 %	3
DNB Norge Selektiv N	511.21	1.00 %	3
DNB Norge Selektiv R	511.21	0.75 %	3
DNB SMB A	209.77	1.42 %	6
DNB SMB N	209.77	1.05 %	6
DNB SMB R	209.77	0.75 %	6
DNB Spare 100	30.54	0.35 %	3
DNB Spare 30	98.73	0.35 %	3
DNB Spare 50	132.19	0.35 %	3
DNB Spare 80	74.11	0.35 %	3
Danske Invest Norge I	77.24	1.50 %	15
Danske Invest Norge II	156.96	1.25 %	15
Danske Invest Norge Vekst	331.88	1.75 %	15.3
Delphi Norge	138.88	2.00 %	0.5
Delphi Norge N	138.88	1.00 %	0.5
Eika Balansert	294.92	1.20 %	8
Eika Norge	313.99	1.50 %	2.5
Eika Spar	863.40	1.50 %	3.2
FIRST Generator A	23.08	1.25 %	10.3
FIRST Generator S	23.08	1.50 %	10.3
FIRST Norge Fokus	26.96	1.25 %	3
FORTE Norge	40.06	2.00 %	3.7
FORTE Tronder	46.49	2.00 %	3.7
Fondsfinans Norge	160.96	1.00 %	5.6
Handelsbanken Norge (NOK)	475.86	2.00 %	5.1
Heimdal Jorde		0.94 %	2.5
Holberg Global Valutasikret A	33.11	1.50 %	2

Holberg Norge A	206.97	1.50 %	5.7
KLP AksjeNorge	831.29	0.75 %	9.1
KLP Kort Horisont Mer Samfunnsansvar	19.61	0.22 %	1.3
KLP Lang Horisont Mer Samfunnsansvar	23.83	0.22 %	1.3
KLP Natid Mer Samfunnsansvar		0.22 %	1.3
KLP Obligasjon 1 Ar Mer Samf.Ansvar	75.78	0.10 %	2.3
Landkreditt Norden Utbytte A	75.44	1.50 %	3
Landkreditt Utbytte A	292.72	1.50 %	9
Nordea Avkastning	529.57	1.50 %	11
Nordea Norge Verdi	552.55	1.50 %	11
Norne Aksje Norge	5.75	1.80 %	1
ODIN Norge A	1171.90	0.75 %	5.5
ODIN Norge B	1171.90	1.00 %	5.5
ODIN Norge C	1171.90	1.50 %	5.5
ODIN Norge D	1171.90	1.00 %	5.5
PLUSS Aksje	17.30	1.20 %	25.1
PLUSS Markedsverdi	20.37	0.90 %	27
Pareto Aksje Norge A	777.00	3.00 %	20.3
Pareto Aksje Norge B	777.00	2.00 %	20.3
Pareto Investment Fund A	93.33	1.80 %	15
SR-Bank Norge A	22.64	1.50 %	3
SR-Bank Norge B	22.64	1.50 %	3
SR-Bank Norge N	22.64	0.85 %	3
SR-Bank Norge U	22.64	0.85 %	3
Sbanken Framgang Sammen	12.73	1.31 %	6
Storebrand Fremtid 80 A		1.10 %	1.1
Storebrand Fremtid 80 N		0.90 %	1.1
Storebrand Global Multifaktor Valutasikret	64.42	0.84 %	4.9
Storebrand Global Multifaktor Valutasikret N	64.42	0.66 %	4.9
Storebrand Norge A	1.60	1.50 %	0.5
Storebrand Norge Fossilfri A	206.92	1.50 %	4.7
Storebrand Norge Fossilfri N	206.92	1.00 %	4.7
Storebrand Norge I	1283.23	0.28 %	17.5
Storebrand Norge N	1.60	1.00 %	0.5
Storebrand Optima Norge A	50.10	1.00 %	10
Storebrand Vekst A	66.97	2.00 %	0.5
Storebrand Vekst N	66.97	1.00 %	0.5
Storebrand Verdi A	83.57	2.00 %	24
Storebrand Verdi N	83.57	1.07 %	24
Verdipapirfondet Norse Utbytte		2.00 %	2.8
Vibrand Kreditt		0.80 %	4
Vibrand Norden	6.78	2.00 %	12.5
XACT Derivat Bear	74.68	0.80 %	6.4

Index funds	Operating Expenses
Alfred Berg Indeks Classic	0.20 %
Alfred Berg Indeks I	0.09 %
DNB Norge Indeks	0.20 %
DNB OBX	0.21 %
KLP AksjeNorge Indeks Acc	0.10 %
KLP AksjeNorge Indeks II	0.18 %
PLUSS Indeks	0.70 %
Storebrand Indeks - Norge A	0.20 %

The table presents all funds in my data sample. Fund TNA is retrieved with the latest updated numbers from the 15th of February. The Operating expenses are given in yearly total expenses for each fund, excluding the performance fee for mutual funds. Years of experience is the number of years the fund manager has worked in this specific fund.

Appendix 2: Descriptive statistics for all funds

Mutual funds	Obs	Average Return	Standard Deviation	Min	Max
Alfred Berg Aktiv	258	0.25 %	2.32 %	-17.90 %	6.49 %
Alfred Berg Gambak	258	0.28 %	2.38 %	-16.55 %	5.90 %
Alfred Berg Gambak N	48	0.37 %	1.55 %	-3.83 %	3.45 %
Alfred Berg Humanfond	258	0.20 %	2.21 %	-16.58 %	6.45 %
Alfred Berg Norge DIST	46	0.38 %	1.56 %	-4.18 %	3.33 %
Alfred Berg Norge [Classic]	258	0.24 %	2.21 %	-16.61 %	6.46 %
C WorldWide Norge	257	0.20 %	2.33 %	-15.92 %	6.85 %
DNB 2020	159	0.06 %	0.35 %	-0.86 %	1.12 %
DNB Aktiv 80	258	0.19 %	1.34 %	-7.31 %	4.20 %
DNB Lev Mer - 2070	158	0.27 %	1.37 %	-7.63 %	4.80 %
DNB Norge	131	0.08 %	1.87 %	-4.44 %	4.50 %
DNB Norge A	127	0.30 %	2.96 %	-17.49 %	7.48 %
DNB Norge N	114	0.26 %	3.07 %	-17.49 %	7.48 %
DNB Norge R	163	0.21 %	2.80 %	-17.47 %	7.48 %
DNB Norge Selektiv A	258	0.26 %	2.65 %	-18.71 %	8.68 %
DNB Norge Selektiv N	115	0.34 %	3.34 %	-18.70 %	8.69 %
DNB Norge Selektiv R	156	0.31 %	2.97 %	-18.70 %	8.69 %
DNB SMB A	258	0.32 %	3.08 %	-20.88 %	11.64 %
DNB SMB N	109	0.44 %	4.17 %	-20.89 %	11.64 %
DNB SMB R	155	0.46 %	3.58 %	-21.13 %	11.69 %
DNB Spare 100	149	0.28 %	1.65 %	-9.15 %	5.42 %
DNB Spare 30	149	0.10 %	0.65 %	-3.81 %	2.15 %
DNB Spare 50	148	0.16 %	0.92 %	-4.75 %	2.99 %
DNB Spare 80	149	0.23 %	1.36 %	-7.37 %	4.51 %
Danske Invest Norge I	256	0.24 %	2.25 %	-16.86 %	6.94 %
Danske Invest Norge II	256	0.25 %	2.25 %	-16.87 %	6.96 %
Danske Invest Norge Vekst	256	0.35 %	2.60 %	-19.25 %	9.96 %
Delphi Norge	259	0.24 %	2.78 %	-18.10 %	8.15 %
Delphi Norge N	74	0.47 %	2.52 %	-6.09 %	7.82 %
Eika Balansert	258	0.10 %	0.95 %	-7.81 %	3.19 %
Eika Norge	258	0.16 %	2.15 %	-14.75 %	6.20 %
Eika Spar	258	0.18 %	1.80 %	-11.78 %	5.29 %
FIRST Generator A	210	0.16 %	4.20 %	-21.56 %	15.87 %
FIRST Generator S	258	0.21 %	3.65 %	-20.20 %	14.96 %
FIRST Norge Fokus	164	0.24 %	2.66 %	-18.09 %	7.48 %
FORTE Norge	258	0.26 %	2.47 %	-16.88 %	6.74 %
FORTE Tronder	258	0.23 %	2.92 %	-23.77 %	10.97 %
Fondsfinans Norge	259	0.23 %	2.64 %	-17.59 %	6.53 %
Handelsbanken Norge (NOK)	30	0.20 %	1.33 %	-2.03 %	3.49 %
Heimdal Jorde	117	0.18 %	1.50 %	-9.00 %	6.19 %

Holberg Global Valutasikret A	108	0.26 %	2.68 %	-11.60 %	7.28 %
Holberg Norge A	259	0.31 %	2.59 %	-19.82 %	10.86 %
KLP AksjeNorge	258	0.22 %	2.44 %	-16.73 %	7.65 %
KLP Kort Horisont Mer Samfunnsansvar	71	0.05 %	0.39 %	-1.18 %	1.38 %
KLP Lang Horisont Mer Samfunnsansvar	71	0.20 %	0.98 %	-2.61 %	3.56 %
KLP Natid Mer Samfunnsansvar	70	-0.01 %	0.19 %	-0.44 %	0.43 %
KLP Obligasjon 1 Ar Mer Samf.Ansvar	119	0.03 %	0.10 %	-0.54 %	0.54 %
Landkreditt Norden Utbytte A	154	0.25 %	1.99 %	-13.10 %	4.58 %
Landkreditt Utbytte A	258	0.25 %	1.90 %	-14.61 %	6.73 %
Nordea Avkastning	259	0.23 %	2.43 %	-19.19 %	7.38 %
Nordea Norge Verdi	259	0.22 %	2.15 %	-17.19 %	6.12 %
Norne Aksje Norge	47	0.31 %	1.90 %	-4.82 %	3.98 %
ODIN Norge A	258	0.24 %	2.19 %	-16.91 %	7.17 %
ODIN Norge B	258	0.23 %	2.20 %	-16.92 %	7.16 %
ODIN Norge C	259	0.22 %	2.19 %	-16.93 %	7.15 %
ODIN Norge D	258	0.23 %	2.19 %	-16.92 %	7.17 %
PLUSS Aksje	259	0.16 %	2.14 %	-14.15 %	5.83 %
PLUSS Markedsverdi	259	0.18 %	2.22 %	-15.12 %	6.28 %
Pareto Aksje Norge A	257	0.21 %	2.35 %	-17.02 %	8.29 %
Pareto Aksje Norge B	257	0.22 %	2.39 %	-17.06 %	8.25 %
Pareto Investment Fund A	257	0.21 %	2.96 %	-19.74 %	9.11 %
SR-Bank Norge A	160	0.38 %	2.68 %	-16.50 %	8.22 %
SR-Bank Norge B	160	0.34 %	2.68 %	-16.50 %	8.21 %
SR-Bank Norge N	33	0.31 %	1.75 %	-3.93 %	3.62 %
SR-Bank Norge U	33	0.31 %	1.76 %	-3.93 %	3.62 %
Sbanken Framgang Sammen	258	0.21 %	2.20 %	-16.59 %	6.44 %
Storebrand Fremtid 80 A	69	0.27 %	1.24 %	-2.79 %	3.65 %
Storebrand Fremtid 80 N	62	0.23 %	1.10 %	-2.47 %	3.65 %
Storebrand Global Multifaktor Valutasikret	251	0.19 %	2.61 %	-15.98 %	10.87 %
Storebrand Global Multifaktor Valutasikret N	188	0.17 %	2.93 %	-15.98 %	10.87 %
Storebrand Norge A	258	0.24 %	2.39 %	-17.31 %	8.08 %
Storebrand Norge Fossilfri A	247	0.27 %	2.06 %	-13.19 %	5.20 %
Storebrand Norge Fossilfri N	62	0.23 %	1.90 %	-4.10 %	4.65 %
Storebrand Norge I	258	0.25 %	2.24 %	-16.08 %	6.97 %
Storebrand Norge N	62	0.35 %	1.96 %	-4.35 %	6.10 %
Storebrand Optima Norge A	113	0.19 %	1.64 %	-4.34 %	4.23 %
Storebrand Vekst A	258	0.20 %	2.58 %	-18.11 %	8.85 %
Storebrand Vekst N	74	0.21 %	2.42 %	-5.99 %	5.90 %
Storebrand Verdi A	258	0.26 %	2.23 %	-16.32 %	7.50 %
Storebrand Verdi N	199	0.29 %	2.42 %	-16.32 %	7.51 %
Verdipapirfondet Norse Utbytte	148	0.34 %	2.05 %	-11.59 %	5.10 %
Vibrand Kreditt	141	0.09 %	0.79 %	-6.40 %	4.43 %
Vibrand Norden	258	0.24 %	2.32 %	-16.12 %	7.18 %
XACT Derivat Bear	31	-0.64 %	2.73 %	-7.36 %	4.74 %

Index funds	**Obs**	**Average Return**	**Standard Deviation**	**Min**	**Max**
Alfred Berg Indeks Classic	259	0.23 %	2.23 %	-15.67 %	6.64 %
Alfred Berg Indeks I	259	0.23 %	2.23 %	-15.67 %	6.64 %
DNB Norge Indeks	259	0.23 %	2.25 %	-15.69 %	6.80 %
DNB OBX	259	0.23 %	2.30 %	-15.69 %	7.27 %
KLP AksjeNorge Indeks Acc	259	0.23 %	2.25 %	-15.76 %	6.78 %
KLP AksjeNorge Indeks II	259	0.23 %	2.25 %	-15.76 %	6.78 %
PLUSS Indeks	254	0.21 %	2.27 %	-15.56 %	7.19 %
Storebrand Indeks - Norge A	259	0.24 %	2.25 %	-15.81 %	6.76 %

This table presents the descriptive statistics for both mutual funds and index funds. The returns are gross return but include income yield from dividend reinvested and interest payments. All numbers are derived from weekly data for the sample period from 17th of February 2017 to 28th of January 2022. The average return, standard deviation, minimum and maximum are presented on a weekly basis.

Appendix 3 – The classical assumptions for regression models

The seven classical assumptions when exercising OLS models:

1. The regression model is linear and is correctly specified.

2. The error term has a zero population mean. To illustrate this, I use the expected error term which is equal to zero: $E(\varepsilon_{it}) = 0$

3. All explanatory variables are uncorrelated with the error term. My explanatory variables are uncorrelated with the error term (ε).

4. No autocorrelation. From *Appendix 4* I find that some of the fund's regression models does not fulfill the assumption of no autocorrelation. This is corrected by using corrected standard errors with a Newey-West estimation.

5. No heteroskedasticity. From *Appendix 4* only 44% of the fund's regression models fulfills this assumption, the majority is heteroskedastic. As with autocorrelation, I also correct for heteroskedasticity using the Newey-West estimation.

6. No multicollinearity. There is no perfect linear function between any of my explanatory variables. This is illustrated in both Table 3 & Table 4 in subsection *6.4.4 Assumption of no multicollinearity*.

7. The error term is normally distributed. From the test in *Appendix 4*, I find that the majority is not normally distributed. But this assumption is termed optional.

A 5% significance level was used for the tests. I need to emphasize that the models could still be used even though some of the assumptions are not fulfilled. The models will still be able to provide results. But depending on which assumption are not fulfilled, it will cause interference with the standard errors. The final results, and also my conclusions, will thus have less validity.

Appendix 4 – Tests for OLS assumptions

Active mutual funds	Skewness & kurtosis for normality P-value for joint test	LM-test for no autocorrelation P-value Breusch-Godfrey	Homoskedasticity P-value White-test
Alfred Berg Aktiv	0.0003	0.7339	0.0000
Alfred Berg Gambak	0.0097	0.7928	0.0061
Alfred Berg Gambak N	0.9535	0.4086	0.9337
Alfred Berg Humanfond	0.0000	0.6719	0.0051
Alfred Berg Norge DIST	0.7049	0.6839	0.1380
Alfred Berg Norge [Classic]	0.0000	0.7064	0.0000
C WorldWide Norge	0.0004	0.9592	0.1907
DNB 2020	0.0000	0.4687	0.0000
DNB Aktiv 80	0.2434	0.6543	0.0133
DNB Lev Mer - 2070	0.0898	0.9343	0.0130
DNB Norge	0.1909	0.7403	0.4912
DNB Norge A	0.9474	0.9177	0.1489
DNB Norge N	0.0000	0.9934	0.9994
DNB Norge R	0.7713	0.7660	0.7621
DNB Norge Selektiv A	0.0000	0.1932	0.0094
DNB Norge Selektiv N	0.0069	0.1578	0.2763
DNB Norge Selektiv R	0.0027	0.1884	0.0337
DNB SMB A	0.0000	0.1774	0.0001
DNB SMB N	0.0014	0.4266	0.0569
DNB SMB R	0.0001	0.4531	0.0014
DNB Spare 100	0.1763	0.9360	0.0028
DNB Spare 30	0.0333	0.8653	0.0005
DNB Spare 50	0.0662	0.8126	0.1631
DNB Spare 80	0.1989	0.9695	0.0182
Danske Invest Norge I	0.0101	0.9316	0.0006
Danske Invest Norge II	0.0083	0.9282	0.0005
Danske Invest Norge Vekst	0.0000	0.7582	0.0000
Delphi Norge	0.0000	0.3206	0.2233
Delphi Norge N	0.0000	0.6036	0.9308
Eika Balansert	0.0003	0.5339	0.0000
Eika Norge	0.2491	0.7066	0.0082
Eika Spar	0.6048	0.2342	0.1413
FIRST Generator A	0.0018	0.5896	0.2151
FIRST Generator S	0.0000	0.4611	0.3630
FIRST Norge Fokus	0.0074	0.4125	0.0021
FORTE Norge	0.0003	0.0930	0.7905
FORTE Tronder	0.0000	0.0051	0.0000
Fondsfinans Norge	0.0001	0.2050	0.7030
Handelsbanken Norge (NOK)	0.7419	0.7281	0.5264
Heimdal Jorde	0.0000	0.4401	0.0001
Holberg Global Valutasikret A	0.0059	0.0005	0.0074

Holberg Norge A	0.0001	0.9464	0.0000
KLP AksjeNorge	0.0421	0.4712	0.0000
KLP Kort Horisont Mer Samfunnsansvar	0.0005	0.0957	0.9540
KLP Lang Horisont Mer Samfunnsansvar	0.2006	0.3982	0.0085
KLP Natid Mer Samfunnsansvar	0.1797	0.0099	0.2630
KLP Obligasjon 1 Ar Mer Samf.Ansvar	0.0000	0.3824	0.0057
Landkreditt Norden Utbytte A	0.0014	0.4549	0.0000
Landkreditt Utbytte A	0.0000	0.7178	0.0078
Nordea Avkastning	0.0019	0.4186	0.0000
Nordea Norge Verdi	0.0000	0.8084	0.0000
Norne Aksje Norge	0.5898	0.9342	0.1624
ODIN Norge A	0.0003	0.7790	0.0000
ODIN Norge B	0.0003	0.7972	0.0000
ODIN Norge C	0.0003	0.7885	0.0000
ODIN Norge D	0.0003	0.7901	0.0000
PLUSS Aksje	0.0082	0.9835	0.1260
PLUSS Markedsverdi	0.0172	0.0297	0.2148
Pareto Aksje Norge A	0.0919	0.6884	0.0042
Pareto Aksje Norge B	0.1052	0.9906	0.0302
Pareto Investment Fund A	0.0012	0.0094	0.0453
SR-Bank Norge A	0.9185	0.2946	0.0577
SR-Bank Norge B	0.0296	0.6069	0.4176
SR-Bank Norge N	0.1819	0.3564	0.1217
SR-Bank Norge U	0.1818	0.3566	0.1220
Sbanken Framgang Sammen	0.0000	0.6953	0.0000
Storebrand Fremtid 80 A	0.2557	0.3628	0.2687
Storebrand Fremtid 80 N	0.8556	0.1724	0.1238
Storebrand Global Multifaktor Valutasikret	0.0000	0.0000	0.0012
Storebrand Global Multifaktor Valutasikret N	0.0000	0.0000	0.0006
Storebrand Norge A	0.0000	0.3144	0.4588
Storebrand Norge Fossilfri A	0.0003	0.8103	0.6510
Storebrand Norge Fossilfri N	0.0002	0.6436	0.9274
Storebrand Norge I	0.0000	0.0794	0.0004
Storebrand Norge N	0.0000	0.6789	0.9315
Storebrand Optima Norge A	0.5829	0.7586	0.7687
Storebrand Vekst A	0.4157	0.1681	0.2343
Storebrand Vekst N	0.4608	0.0382	0.9682
Storebrand Verdi A	0.2083	0.7100	0.0004
Storebrand Verdi N	0.8662	0.6072	0.0016
Verdipapirfondet Norse Utbytte	0.6153	0.2152	0.0397
Vibrand Kreditt	0.0000	0.0178	0.0002
Vibrand Norden	0.0303	0.9295	0.0293
XACT Derivat Bear	0.3485	0.0940	0.3162

Appendix 5 – Individual regressions for all mutual funds

Active mutual funds	α	MKT-RF	SMB	HML	R^2
Alfred Berg Aktiv	1.57 %	1.0102***	0.0751***	-0.0175	0.9432
Alfred Berg Gambak	3.71 %	1.0191***	0.2158***	-0.0563**	0.8978
Alfred Berg Gambak N	10.37 %*	-0.9068***	0.0826	-0.0483	0.8664
Alfred Berg Humanfond	-1.03 %	0.9650***	0.0099	-0.0190	0.9557
Alfred Berg Norge DIST	5.33 %*	0.9260***	0.0110	0.0270	0.9421
Alfred Berg Norge [Classic]	0.52 %	0.9752***	0.0259	-0.0135	0.9702
C WorldWide Norge	-2.06 %	1.0255***	-0.0014	-0.0198	0.9591
DNB 2020	1.05 %	0.1257***	-0.0379	0.0113	0.4978
DNB Aktiv 80	4.79 %*	0.4667***	0.1908***	-0.0281	0.6007
DNB Lev Mer – 2070	8.67 %**	0.4146***	0.1926***	-0.0505	0.5836
DNB Norge	-2.57 %	1.0625***	0.0942***	0.0758***	0.9330
DNB Norge A	-1.03 %	1.0646***	0.0794**	0.0579***	0.9786
DNB Norge N	0.52 %	1.0632***	0.0996***	0.0514***	0.9716
DNB Norge R	-2.06 %	1.0721***	0.0859***	0.0719***	0.9733
DNB Norge Selektiv A	1.05 %	1.1191***	0.1491***	0.0113	0.8910
DNB Norge Selektiv N	3.71 %	1.1223***	0.2076***	-0.0299	0.8852
DNB Norge Selektiv R	1.05 %	1.1133***	0.1664***	0.0039	0.9055
DNB SMB A	6.43 %	1.1603***	0.5955***	0.0007	0.7345
DNB SMB N	9.80 %	1.2320***	0.6402***	-0.0632	0.7660
DNB SMB R	8.67 %	1.2196***	0.6584***	-0.0122	0.7801
DNB Spare 100	8.67 %*	0.4871***	0.2021**	-0.0614	0.5771
DNB Spare 30	2.63 %	0.1887***	0.1181***	-0.0207	0.6075
DNB Spare 50	4.25 %*	0.2774***	0.1467***	-0.0322	0.6303
DNB Spare 80	6.99 %*	0.4078***	0.1837***	-0.0499*	0.6014
Danske Invest Norge I	0.52 %	0.9673***	0.0456	0.0353**	0.9450
Danske Invest Norge II	1.05 %	0.9677***	0.0473	0.0351**	0.9456
Danske Invest Norge Vekst	5.88 %*	1.0962***	0.2729***	-0.0678**	0.8674
Delphi Norge	1.05 %	1.1483***	0.2736***	0.0467	0.8700
Delphi Norge N	3.17 %	1.1789***	0.2938***	-0.0392	0.8324
Eika Balansert	0.52 %	0.3948***	0.0919***	-0.0077	0.8458
Eika Norge	-2.06 %*	0.9335***	0.0895***	0.0201	0.9563
Eika Spar	1.05 %	0.7405***	0.1487***	0.0014	0.8467
FIRST Generator A	-5.07 %	1.4372***	0.3837***	0.3542***	0.7958
FIRST Generator S	-2.57 %	1.3555***	0.2975***	0.2799***	0.7878
FIRST Norge Fokus	1.05 %	1.0072***	0.1519**	-0.0159	0.9108
FORTE Norge	3.17 %	1.0067***	0.2319***	0.0587**	0.8557
FORTE Tronder	-0.52 %	1.1635***	0.2123**	0.1370***	0.8511
Fondsfinans Norge	1.05 %	1.0622***	0.1806***	0.1649***	0.8867
Handelsbanken Norge (NOK)	-1.55 %	1.0072***	-0.0104	-0.0583	0.7993
Heimdal Jorde	3.71 %	0.3731***	0.1985	0.0364	0.5230
Holberg Global Valutasikret A	8.11 %	0.6970***	0.3655**	-0.1884***	0.6218

Holberg Norge A	5.88 %*	1.0245***	0.2508***	0.1287***	0.8363
KLP AksjeNorge	-0.52 %	1.0451***	0.1072***	0.1034***	0.9706
KLP Kort Horisont Mer Samfunnsansvar	2.10 %	0.1047***	0.0342	-0.0300**	0.3414
KLP Lang Horisont Mer Samfunnsansvar	9.80 %*	0.3346***	0.1348**	-0.0992***	0.5669
KLP Natid Mer Samfunnsansvar	0.52 %	0.0105	-0.0027	-0.0202**	0.0933
KLP Obligasjon 1 Ar Mer Samf.Ansvar	1.05 %	0.0135*	0.0074	-0.0015	0.1337
Landkreditt Norden Utbytte A	6.43 %	0.6033***	0.1253	-0.1427***	0.5757
Landkreditt Utbytte A	4.79 %*	0.7765***	0.1395**	-0.0324	0.8143
Nordea Avkastning	1.57 %	1.0338***	0.2101***	0.0935***	0.9448
Nordea Norge Verdi	2.63 %	0.8696***	0.2331***	0.0770***	0.8575
Norne Aksje Norge	4.25 %	1.1356***	0.2443**	0.0100	0.8151
ODIN Norge A	1.57 %	0.9328***	0.0674*	0.0286	0.9218
ODIN Norge B	1.57 %	0.9328***	0.0682*	0.0291	0.9220
ODIN Norge C	1.05 %	0.9328***	0.0677*	0.0289	0.9218
ODIN Norge D	1.57 %	0.9328***	0.0675*	0.0287	0.9219
PLUSS Aksje	-2.57 %	0.9243***	-0.0040	0.0067	0.9485
PLUSS Markedsverdi	-2.06 %	0.9643***	-0.0370**	0.0294***	0.9728
Pareto Aksje Norge A	-0.52 %	0.9519***	0.0779*	0.1265***	0.8901
Pareto Aksje Norge B	0.52 %	0.9689***	0.0895**	0.1300***	0.8939
Pareto Investment Fund A	-1.03 %	1.1831***	0.4382***	0.1092***	0.8384
SR-Bank Norge A	5.33 %*	0.9939***	0.1214**	0.1007***	0.9229
SR-Bank Norge B	3.17 %	0.9951***	0.1189**	0.0844***	0.9144
SR-Bank Norge N	8.11 %	1.0346***	0.2610**	0.1337***	0.8257
SR-Bank Norge U	8.11 %	1.0346***	0.2610**	0.1337***	0.8256
Sbanken Framgang Sammen	-0.52 %	0.9651***	0.0123	-0.0183	0.9612
Storebrand Fremtid 80 A	12.69 %**	0.4771***	0.1869***	-0.1299***	0.6597
Storebrand Fremtid 80 N	12.11 %**	0.4452***	0.1634**	-0.1321***	0.5775
Storebrand Global Multifaktor Valutasikret	1.05 %	0.8674***	0.3707**	0.0518	0.5846
Storebrand Global Multifaktor Valutasikret N	0.52 %	0.8895***	0.4226**	0.0932	0.6019
Storebrand Norge A	0.52 %	1.0503***	0.8957***	-0.0273	0.9475
Storebrand Norge Fossilfri A	3.17 %*	0.8996***	0.1185***	-0.1989***	0.9238
Storebrand Norge Fossilfri N	4.25 %	1.0123***	0.1091*	-0.2321***	0.8915
Storebrand Norge I	0.52 %	0.9727***	-0.0469**	0.0366***	0.9742
Storebrand Norge N	-3.58 %	1.1193***	0.2047***	0.0259	0.8701
Storebrand Optima Norge A	-1.55 %	0.9194***	-0.0715	-0.0584*	0.8792
Storebrand Vekst A	-0.52 %	1.0409***	0.3276***	-0.0116	0.8055
Storebrand Vekst N	-6.54 %	1.1018***	0.2259***	-0.0831	0.7998
Storebrand Verdi A	2.10 %	0.9410***	-0.0026	0.0670***	0.9381
Storebrand Verdi N	2.63 %	0.9471***	-0.0005	0.0737***	0.9440
Verdipapirfondet Norse Utbytte	8.11 %***	0.7410***	0.0830**	0.0224	0.8807
Vibrand Kreditt	3.17 %	0.1128**	0.1237	0.0285	0.2081
Vibrand Norden	2.63 %	0.9059***	0.1332**	0.1111***	0.8207
XACT Derivat Bear	-2.06 %	-1.9993***	0.6237***	-0.0191	0.9515

*The table presents individual regressions with the 3-factor model for all mutual funds. Alphas are annualized. T-values and thus significance measured with p-values, are adjusted with the Newey-West corrected standard errors. R^2 is retrieved from the regression models for all mutual funds. Coefficients are presented for each factor. Significance is illustrated with p-values: *p < 0.1, **p < 0.05, ***p < 0.01*

Appendix 6 – Sharpe Ratio of all mutual funds

Active mutual funds	Sharpe Ratio	Active mutual funds	Sharpe Ratio
Alfred Berg Aktiv	0.74	KLP AksjeNorge	0.62
Alfred Berg Gambak	0.82	KLP Kort Horisont Mer Samfunnsansvar	0.73
Alfred Berg Gambak N	**1.67**	**KLP Lang Horisont Mer Samfunnsansvar**	**1.40**
Alfred Berg Humanfond	0.62	KLP Natid Mer Samfunnsansvar	-0.77
Alfred Berg Norge DIST	**1.71**	**KLP Obligasjon 1 Ar Mer Samf.Ansvar**	**1.41**
Alfred Berg Norge [Classic]	0.75	Landkreditt Norden Utbytte A	0.87
C WorldWide Norge	0.59	Landkreditt Utbytte A	0.91
DNB 2020	**1.02**	Nordea Avkastning	0.65
DNB Aktiv 80	0.97	Nordea Norge Verdi	0.70
DNB Lev Mer - 2070	**1.37**	**Norne Aksje Norge**	**1.14**
DNB Norge	0.27	ODIN Norge A	0.76
DNB Norge A	0.71	ODIN Norge B	0.72
DNB Norge N	0.59	ODIN Norge C	0.69
DNB Norge R	0.51	ODIN Norge D	0.72
DNB Norge Selektiv A	0.68	PLUSS Aksje	0.50
DNB Norge Selektiv N	0.71	PLUSS Markedsverdi	0.55
DNB Norge Selektiv R	0.73	Pareto Aksje Norge A	0.61
DNB SMB A	0.72	Pareto Aksje Norge B	0.63
DNB SMB N	0.74	Pareto Investment Fund A	0.49
DNB SMB R	0.91	SR-Bank Norge A	0.99
DNB Spare 100	**1.18**	SR-Bank Norge B	0.89
DNB Spare 30	0.99	**SR-Bank Norge N**	**1.23**
DNB Spare 50	**1.17**	**SR-Bank Norge U**	**1.23**
DNB Spare 80	**1.16**	Sbanken Framgang Sammen	0.65
Danske Invest Norge I	0.74	**Storebrand Fremtid 80 A**	**1.51**
Danske Invest Norge II	0.77	**Storebrand Fremtid 80 N**	**1.44**
Danske Invest Norge Vekst	0.94	Storebrand Global Multifaktor Valutasikret	0.50
Delphi Norge	0.60	Storebrand Global Multifaktor Valutasikret N	0.39
Delphi Norge N	**1.32**	Storebrand Norge A	0.69
Eika Balansert	0.68	Storebrand Norge Fossilfri A	0.91
Eika Norge	0.50	Storebrand Norge Fossilfri N	0.83
Eika Spar	0.68	Storebrand Norge I	0.77
FIRST Generator A	0.26	**Storebrand Norge N**	**1.25**
FIRST Generator S	0.39	Storebrand Optima Norge A	0.79
FIRST Norge Fokus	0.62	Storebrand Vekst A	0.53
FORTE Norge	0.73	Storebrand Vekst N	0.59
FORTE Tronder	0.54	Storebrand Verdi A	0.81
Fondsfinans Norge	0.60	Storebrand Verdi N	0.83
Handelsbanken Norge (NOK)	**1.03**	**Verdipapirfondet Norse Utbytte**	**1.16**
Heimdal Jorde	0.82	Vibrand Kreditt	0.73
Holberg Global Valutasikret A	0.67	Vibrand Norden	0.71
Holberg Norge A	0.83	XACT Derivat Bear	-1.72

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